Essays on Reputation in Online Marketplaces

by

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Published and Submitted Content

The two chapters of this thesis have been published online as working papers and conference papers. In particular,

1. A previous version of Chapter 1 has been published as:

   Rossi, Michelangelo (2019) : How Does Competition Affect Reputation Concerns? Theory and Evidence from Airbnb, CESifo Working Paper, No. 7972, Center for Economic Studies and ifo Institute (CESifo), Munich;

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   The material from this source included in this thesis is not singled out with typographic means and references;

2. A previous version of Chapter 2 appeared as a conference paper for the 18th Annual International Industrial Organization Conference;

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   The material from this source included in this thesis is not singled out with typographic means and references.

Other Research Merits

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Abstract

Would you ever rent a house you have never seen; whose owner you have never met; in a city you have never visited? And again: would you ever pay upfront to a person you do not know, and you will never meet, who promise to deliver an object you have never seen? A few decades ago the answers to these questions would have been negative for most customers. Conversely, nowadays millions of users rely on digital platforms, such as Airbnb and eBay, to get services with the same characteristics as those described by the previous two questions. How was that possible? How did users around the world start to trust each other after millennia of skepticism and malevolence?

An answer to such questions relies on the innovative way digital marketplaces use to reduce the asymmetry of information between parties: review systems. In almost all digital platforms, users can review the services they have experienced providing new pieces of information to prospective users. Accordingly, reviews reduce the uncertainty about sellers' quality since each feedback increases the precision of buyers' estimates. Besides, reviews also discipline sellers' ongoing behavior with the potential punishment of negative feedback. Still, signaling quality and monitoring sellers' behavior are two separate tasks. From a microeconomic perspective, reviews reduce adverse selection effects by signaling sellers' quality, whereas monitoring behavior affects moral hazard issues.

In this dissertation I study the power, and the limits, of review systems to reduce these two types of asymmetry of information: adverse selection and moral hazard. In the two chapters of this thesis, I examine both signaling and monitoring tasks.[1]

In the first chapter, *How Does Competition Affect Reputation Concerns? Theory and Evidence from Airbnb*, I show how changes in the number of close competitors affect the power of reputation to induce sellers to exert effort. The impact of competition on sellers' incentives is theoretically ambiguous. More competition disciplines sellers, but, at the same time, it erodes reputational premia. This paper identifies empirically whether one effect dominates the other using data from Airbnb. To guide the empirical analysis, I develop a model of reputation with frictional matching between the two sides of the market. Here the relative number of hosts and guests affects the value of building a reputation through effort. In this specific framework, more competition depresses hosts' profits and leads hosts to reduce effort. I test the model's prediction exploiting a change in regulation for Airbnb listings effective in San Francisco in 2017. I identify a negative causal effect of competition on ratings about hosts' effort. These findings suggest

[1] I reviewed the economic literature regarding the role of review systems in digital platforms in *Asymmetric Information and Review Systems: The Challenge of Digital Platforms* published in 2018 as a chapter of the book *Economic Analysis of the Digital Revolution* (edited by Prof. Juan José Ganuza and Prof. Gerard Llobet).

that more competition may erode incentives for high-quality services in frictional marketplaces where sellers' performances depend on reputation.

In the second chapter, *Quality Disclosures and Disappointment: Evidence from the Academy Awards*, I study the impact of quality disclosures on buyers' rating behavior using data from an online recommender system. Disclosures may alter expectations on sellers' quality and affect buyers' rating behavior. In particular, if buyers' utility depends on a reference point induced by their expectations, a positive disclosure of quality such as an award may lead to buyers' disappointment and it negatively influences their ratings. I identify the disappointment effect in moviegoers' ratings originated from the rise in expectations due to movies' nominations for the Academy of Motion Picture Arts and Sciences awards. I control for the selection of moviegoers who watch and rate movies before or after nominations with a non-parametric matching technique. After nominations, ratings for nominated movies significantly drop relative to ratings for movies that were not nominated. This short-term disappointment effect reduces the rating premium of nominated movies by more than five percent.

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Chapter 1

How Does Competition Affect Reputation Concerns? Theory and Evidence from Airbnb

1.1 Introduction

Digital platforms rely on review systems to ensure the quality of their services and to provide incentives for sellers to exert effort. Reviews reveal sellers' past performances and form their reputation. Thus, sellers' concerns for a good reputation are one of the key ingredients for the quality of online transactions and the success of digital marketplaces.

This paper studies how changes in the number of competitors affect the power of reputation to provide incentives for sellers to exert effort. The effects of competition on the sellers' incentives are theoretically ambiguous (Bar-Isaac, 2005). More competition may help to discipline sellers, but, at the same time, it erodes reputational premia. Understanding which of the two effects dominates empirically is a relevant question, not only for the design of digital platforms, but also for other settings in which sellers' quality is unknown and their performances depend on reputation. This feature is common to several markets involving experience goods and services such as hospitals, restaurants, or schools. Yet, the process of reputation building is particularly relevant in online marketplaces since review systems provide an observable measure of sellers' reputation and effort.

I empirically address this research question using data from one of the fastest-growing online platforms: Airbnb. This setting is of special interest since the enormous growth in the number of hosts on the platform has attracted considerable attention from local governments and regulators. Previous works have shown that the entry of Airbnb hosts in a city expands the number of available rooms, and reduces hotels' profits, with a positive effect on consumers' welfare (Zervas et al., 2017; and Farronato and Fradkin, 2018). Yet, in addition to the disciplining impact of competition on prices, an increase in the number of competitors may also impact hosts' incentives to exert effort affecting the quality of platform's services. To the best of my knowledge, this is the first paper to identify the causal impact of the number of competitors on the incentives to exert effort in online marketplaces: my findings show that, when the number of competitors increases, hosts exert less effort and their profits reduce.

I develop a model of reputation building with congested marketplaces and frictional matching to accommodate the feature of digital platforms, and inform my empirical analysis. In this framework, the number of hosts and guests on the two sides of the market (the market tightness) impacts the reputation returns of hosts' effort. The model predicts that, when the number of competitors decreases, hosts' profits increase and hosts exert more effort. With fewer competitors, hosts have higher probability to be matched with a guest and can charge higher prices. However, the price elasticity of hosts' demand depends on their reputation. In particular, the probability to be matched with a guest is less elastic to variations in prices for hosts with good reputation. Accordingly, the premium of exerting effort (and having good reputation) increases when the number of competitors is lower: hosts with good reputation can post higher prices with a lower reduction in their demand. Thus, hosts exert more effort when the number of competitors decreases.

In order to test the model's prediction, I analyze empirically the relationship between the effort exerted by Airbnb hosts and the number of their competitors. I measure hosts' effort by studying ratings such as *communication* and *check-in* that are specifically related to hosts' actions. Moreover, to measure the number of competitors for each host, I create host-specific consideration sets by counting the number of listings surrounding each host within a radius of 0.5, 1, and 2 kilometers. Doing so, I assume that Airbnb hosts compete more strongly with listings that are closely located to them, relative to those further away. This is in line with Zervas et al. (2017) who show that the impact of Airbnb entry on hotels' revenues is sensitive to the distance between hotels and Airbnb listings.

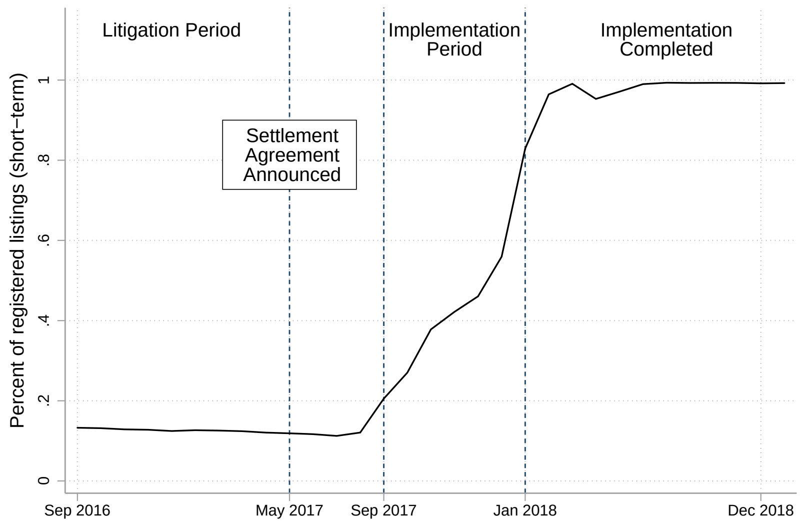
My identification strategy exploits a unique quasi-experiment to isolate the effect of changes in the number of competitors from other confounders. In particular, I take advantage of a regulatory enforcement on short-term rentals that occurred in San Francisco in 2017.

In 2015, San Francisco was the third US city in terms of active Airbnb listings after New York and Los Angeles (Lane et al., 2016). From that year, the San Francisco City Council imposed several restrictions and a formal registration for short-term rentals on digital platforms.[1] Yet, the regulation started to be effectively enforced only two years later, when Airbnb signed a Settlement Agreement with the City Council in May 2017. Accordingly, the platform has been actively engaged in the listings' registration process since September 2017. As shown in Figure 1.1, the percentage of Airbnb listings offering short-term lodging formally registered at the City Council Office dramatically increased from less than 15 percent in September 2017 to 100 percent in February 2018: hosts started to register, and those who could not, exited the platform. As a result, a few months after September 2017, the number of Airbnb listings offering short-term lodging halved, dropping from about 8,000 units in September 2017 to less than 4,000 in February 2018 (see Figure 1.2).

I exploit this regulatory enforcement as an exogenous shift in the number of listings surrounding each host. I focus on hosts renting short-term that were present on the platform both before and after the Settlement Agreement. By such selection, I abstract from hosts' decision to enter or exit due to the regulation enforcement. All hosts renting short-term in San

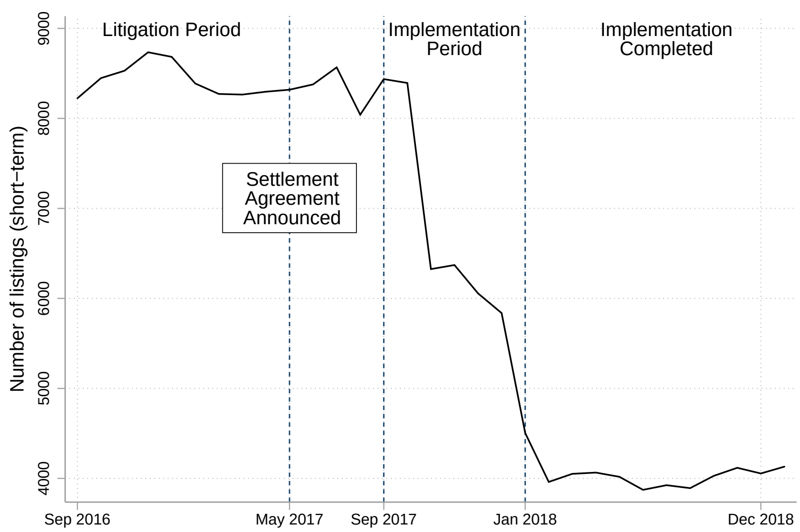
[1]Rentals are considered "short-term" if the properties are rented for less than 30 consecutive nights at a time.

Figure 1.1: Percent of Registered Airbnb Listings over Time



Note: The figure plots the percentage of Airbnb listings offering short-term lodging that displayed a registration number in San Francisco over time from September 2016 to January 2019. The three vertical lines regard the timing of the Settlement Agreement between the San Francisco City Council and Airbnb. The agreement was signed and announced in May 2017 and it has been effective since September 2017. According to the resolution, from January 2018 all eligible Airbnb listings should be registered.

Figure 1.2: Short-term Airbnb Listings over Time



Note: The figure plots the total number of Airbnb listings offering short-term lodging in San Francisco over time from September 2016 to January 2019. The three vertical lines regard the timing of the Settlement Agreement between the San Francisco City Council and Airbnb. The agreement was signed in May 2017 and it has been effective since September 2017. According to the resolution, from January 2018 all eligible Airbnb listings should be registered.

Francisco are affected by the Settlement Agreement. On the other hand, the exposure to this "shock" differs since the variation in the number of competitors is heterogeneous across hosts. I take advantage of this heterogeneity in the treatment. To measure the exposure of each host, I use the percentage of listings surrounding each host that were already registered in September 2017. For higher values of this percentage, fewer listings are likely to exit after the Settlement Agreement since they were already complying with the regulation. I employ this measure as a predictor for the variation in the number of listings surrounding each host after the Settlement Agreement.

Therefore, I identify the effect of variations in the number of competitors by using the differential changes in the exposure across listings over time. The core identifying assumption of this design shares the intuition of a difference in differences estimator with a continuous treatment. However, the identification is based on an instrumental variable regression where the excluded instrument is given by the interaction between the measure of exposure (the percentage of listings already registered in September 2017) and time.

The results show a statistically significant negative relationship between the number of competitors and hosts' effort. I corroborate this result studying variations in hosts' profits and in the monetary value of reputation. With the same identification strategy, I find that less competition increases profits, so that hosts have higher incentives to exert effort. Moreover, since fewer hosts are going to have good reputation, I show evidence that the signaling effect of reputation is stronger in more competitive frameworks.

This paper makes contributions to both the empirical and theoretical literatures on reputation. To the best of my knowledge, there are no studies that investigate empirically the relationship between competition and sellers' reputational incentives to exert effort. The empirical literature about reputation has grown in past years with a particular focus on online settings. Still, the majority of the empirical papers study the impact of online feedback on sellers' profits and they do not specify the mechanism behind this effect. Cabral (2012) and Tadelis (2016) give excellent and comprehensive reviews of the empirical literature on this topic.

The closer paper to mine is Elfenbein et al. (2015). They study the effect of quality certification on the probability to sell an item for eBay sellers. Their results show that the positive effect of certification is higher in more competitive settings and when certification is scarce. They do not specifically study sellers' incentives to exert effort, although their main result is in line with a negative relationship between the number of competitors and sellers' effort. With more competition, fewer sellers exert effort, thus good reputation is more scarse and its signaling power is higher. The online setting I use to address my question (Airbnb) presents clear methodological advantages relative to Elfenbein et al. (2015). Thanks to the multiple components of the Airbnb review system, I can use ratings regarding *communication* and *check-in* as a proxy for hosts' effort. Moreover, thanks to the information regarding the geographical location of each Airbnb host, I can exploit the heterogeneous impact of the regulation enforcement for causal identification.

Only recently, a few papers analyze the role of review systems to reduce asymmetries of information in contexts with adverse selection, or moral hazard. These papers focus on the design of online review systems and they do not study the role of competition on sellers' incentives to exert effort. Klein et al. (2016) and Hui et al. (2016a) take advantage of a variation in the eBay review system implemented in 2008 to study changes in eBay sellers' performance. The modification in the review system reduced buyers' fear of retaliation by sellers and improved the transparency of the online feedback. While Klein et al. (2016) claim that this change induced a disciplining effect on sellers' behavior (moral hazard), Hui et al. (2016a) attribute the improvement to seller's selection (adverse selection). In the Airbnb setting, Proserpio et al. (2018) show that members' reciprocity is relevant and users can induce others to behave well by exerting more effort themselves.

From a theoretical perspective, the relationship between competition and sellers' incentives to exert effort is ambiguous. To guide my empirical strategy, I present a model of reputation building that captures the frictional nature of transactions in digital platforms. The model highlights the theoretical mechanism behind the empirical results and it helps to connect the variations in the number of competitors with hosts' effort, profits, and the value of reputation. A few theoretical papers have investigated the relationship between competition and sellers' incentives to exert effort. Most previous reputation models studied the repeated effort choices by a long-lived monopoly seller meeting short-lived buyers in every period. For a comprehensive review of the theoretical literature regarding reputation, see Bar-Isaac and Tadelis (2008). I am aware of only two papers, Kranton (2003) and Bar-Isaac (2005), that explicitly investigate how variations in the extent of competition affect sellers' incentives to exert effort. Kranton (2003) studies the decisions to provide high or low quality goods by a finite number of firms competing in a repeated game. She assumes that, after a firm produces low quality, its future profits are null, independently of competition. Accordingly, an increase in the number of competitors only reduces the benefits of having reputation for high quality and it results in lower incentives to exert effort. Bar-Isaac (2005) allows firms' profits to depend on the number of competitors after a firm produces low quality. As a result, the effects of competition on effort are ambiguous. With a higher degree of competition, profits with reputation for low quality are lower (competition disciplines agents), but, at the same time, profits with reputation for high quality are also lower (competition erodes reputational premia). In contrast with these two papers, my model considers a directed search framework where the matching between hosts and guests is frictional. This is in line with the recent empirical research on online marketplaces that emphasizes how digital platforms are inherently frictional settings (Cullen and Farronato, 2014, Fradkin, 2015, Fradkin, 2017, and Horton, 2019). Guests direct their search to hosts after observing prices and their past effort choices. Accordingly, hosts who exerted effort in the past can charge higher prices and have higher probability to be matched with guests. Conversely, hosts who did not exert effort have to charge lower prices to make guests indifferent at the moment of choosing where to direct their search. However, the price elasticity of hosts' probability to be matched with a guest depends on hosts' reputation. In particular, using standard assumptions on the matching function between hosts and guests, I can show that hosts' matching probability is less elastic to price changes when hosts have good reputation: hosts can post higher prices suffering a lower reduction in their demand when they have good reputation. Therefore, in my model, more competitors lead to lower profits independently of the current hosts' reputation (as in Bar-Isaac (2005)). Yet, the negative effect is stronger for hosts who did not exert any effort in the past: hence, competition erodes the power of reputation to discipline hosts' behavior.

Outside the literature on reputation, several papers analyze the effects of competition on firms' investment decision. Aghion et al. (2001) and Aghion et al. (2005) study the relationship between product market competition and innovation and show empirical evidence of an inverted-U relationship using aggregate data on several industries. In monopolistic settings, firms' investments are low and more competition is beneficial for innovation. Yet, when the starting level of competition is high, an increase in competition may be detrimental. From this perspective, my paper studies a specific type of investment (hosts' effort) that each host decides to make at every transaction, and whose returns are only in terms of reputation. Accordingly, the contribution of this paper to the literature regarding competition and investment is twofold: first, I analyze a context (digital platforms) and a type of investment (hosts' effort) that have never been studied before. Then, I provide a methodological contribution since I identify the causal impact of the number of competitors on hosts' effort exploiting a unique quasi-experiment.

The rest of the paper is organized as follows. Section 1.2 describes the theoretical model and the testable predictions. In Section 1.3, first I provide some background context regarding Airbnb. Then, I illustrate the change in the institutional setting regarding Airbnb hosts regulation in San Francisco in September 2017. Next, I present the dataset. I discuss my identification strategy in Section 1.4. Section 1.5 provides the main empirical findings. In Section 1.6, I show further results in line with the theory. I proceed with the robustness checks in Section 1.7. Section 1.8 concludes. All the proofs and additional tables are in Appendix.

1.2 Model

In this Section, I present the theoretical framework underlying my analysis. This context focuses on the incentives by sellers (in this case, Airbnb hosts) to build a reputation and how changes in the number of close competitors can affect these incentives. To do so, I impose that hosts stay in the market only for two periods; and reputation is the only source of heterogeneity among hosts.

Restricting on a two-period model simplifies the analysis since hosts have no incentives to build a reputation at the end of their life (in the second period). Thus, all the relevant "action" in the model occurs in period 1. This decreasing patterns of the reputation concerns is not altered by adding further life periods, or by allowing hosts to live for an infinite time. Moreover, focusing on a period of reputation building − when hosts exert effort − followed by a period of reputation milking − when hosts shirk and exploit their established reputation − seems to be in line with the relatively short lifespan of the great majority of Airbnb hosts on the platform, as I highlight in Section 1.3.

A second assumption of the model regards hosts' homogeneity: apart from their reputation about the propensity to exert effort, all hosts are homogeneous. Obviously, Airbnb hosts differ in multiple dimensions apart from their reputation, and guests are likely to value other specifics such as the location of the listings. However, I can assume that the interested guests have already narrowed down their search on those listings with certain characteristics, such as the same neighborhood. Thus, at this point of their search, the listings in their consideration sets are homogeneous − they are *close* competitors − and the only relevant differences are about hosts' reputation.

Therefore, the predictions of my model regard the effect of variations in the number of close competitors (with similar observable characteristics) over the process of reputation building. This feature of the model is particularly related with the empirical design I propose in Section 1.4: there, I exploit variations in the number of competitors that are located within 0.5, 1, and 2 kilometers of each host.

The Section proceeds as follows. First, I describe the model environment. I show the agents' characteristics and payoffs; and I clarify the role of frictions with the assumptions regarding the matching function. Then, I present the timing of agents' interactions and the equilibrium concept. Finally, I characterize the equilibrium allocation and propose the main testable predictions of the model. All proofs are in Appendix 1.9.

1.2.1 Model Environment

The market lasts two periods. Hosts and guests populate the two sides of the market. Each guest (he) is willing to rent a house, whereas each host (she) owns a house and can rent it to one guest only.

In both periods there is an infinite population of hosts who can potentially enter the market. Hosts who enter in the first period stay in the market until the second period. To enter the market, hosts pay entry costs, f. Once she entered, a host posts a price p, and, in case of a match with a guest, decides whether to exert effort or not: $e = \{0, 1\}$. A host's cost of effort, c, is realized if a host is matched and it is permanent across periods. The cost can take two values: $c = \{0, k\}$ with $k > 0$. Hosts draw $c = 0$ with probability π. The cost is the host's private information, whereas the probability π is common knowledge for hosts and guests.

A unit mass of guests is present in the market in period 1, and a measure G is present in period 2. Guests are homogeneous and the gross utility from a transaction, u, depends on host's effort and price: $u = ae + b - p$, with $a, b \geq 0$. b represents the benchmark utility that guests obtain from a transaction when hosts do not exert effort. The ex-post surplus of a transaction is defined by the sum of guest's utility and hosts' profit. If the host exerts effort, $e = 1$, the ex-post surplus is $(a + b - p) + (p - c) = a + b - c$. If the host does not exert effort, $e = 0$, the ex-post surplus is $(b - p) + p = b$. In order to guarantee the efficiency of exerting effort $e = 1$, I assume that $a - c > 0$ and that hosts always exert effort $e = 1$ if they draw $c = 0$.

The matching process between hosts and guests is frictional. In line with the directed competitive search literature, market frictions are captured by a matching function M. With a measure h of hosts and g of guests present in the market, a measure $M(h, g) \leq \min(h, g)$ of matches is formed. Assuming constant returns to scale in the matching function, the agents' probability of transacting can be determined as a function of the ratio between guests and hosts, denoted as the market tightness: $\theta = \frac{g}{h}$.

The hosts' probability of transacting when the market tightness is θ is defined as $\alpha(\theta) \equiv \frac{M(h,g)}{h}$. Whereas the guests' probability is defined as $\frac{\alpha(\theta)}{\theta} \equiv \frac{M(h,g)}{g}$. I impose the following conditions on the function $\alpha(\theta)$:

Assumption 1. *For all $\theta \in [0, \infty)$:*

1. *$\alpha(\theta) \in [0, 1]$ and $\frac{\alpha(\theta)}{\theta} \in [0, 1]$;*

2. *$\alpha(\theta)$ is continuous, strictly increasing, twice differentiable, and strictly concave;*

3. *$\alpha(\theta) - \theta\alpha'(\theta) > 0$;*

4. *$\alpha(\infty) = \alpha'(0) = 1$ and $\alpha(0) = \lim_{\theta\to\infty} \theta\alpha'(\theta) = 0$.*

Assumption 1 is standard in the directed search literature[2]. In particular, $\alpha'(\theta) > 0$ and $\alpha(\theta) - \theta\alpha'(\theta) > 0$ state that, when the number of guests over hosts increases, the host matching probability strictly increases and the guest matching probability strictly decreases. The expected payoffs of hosts and guests can be defined in terms of the host effort and pricing decisions and the probability of having a transaction. In each period, the expected profit for hosts is:

$$\Pi = (p - ce)\alpha(\theta);$$

whereas the expected utility for guests depends on the probability to have a transactions and their beliefs regarding host's effort μ:

$$U = (a\mu + b - p)\frac{\alpha(\theta)}{\theta}.$$

The timing of the model is the following. In period 1:

1. Each host decides to enter the market;
2. Each host posts price: $p_1 \in \mathbb{R}^+$;
3. Guests form beliefs about the hosts' expected effort decision observing p_1: $\mu_1(p_1)$;
4. Guests choose where to direct their search and matches are formed;[3]
5. Each host matched with a guest draws the cost of effort c;
6. Each host chooses whether or not to exert effort: $e_1(c, p_1)$;
7. Transactions occur.

At the end of period 1, a history h is formed for each host and it is public information. If the host had a transaction, her history is composed by the effort exerted, $h = (e_1(c))$. If the host did not have a transaction, her history is composed by the information that the host had no guests: $h = (\emptyset)$. Hosts who enter in period 2 have a blank history $h = (\emptyset)$.

After observing histories, guests form interim beliefs $\bar{\mu}_2(h)$ about hosts effort decision in next period.

In period 2, the same timing applies. However, guests update their interim beliefs about hosts' effort observing current prices:

[2] Delacroix and Shi (2013) and Shi and Delacroix (2018) extensively discuss the class of matching functions satisfying Assumption 1 in the literature.

[3] I do not explicitly model the search process by guests. Depending on how the market is organized, different matching functions (all satisfying Assumption 1) can be micro-founded. For further details, see Peters (1991), Burdett et al. (1995) and Burdett et al. (2001).

1. Each host decides to enter the market;
2. Each host posts price: $p_2(c, h) \in \mathbb{R}^+$;
3. Guests update interim beliefs about hosts' expected effort decision observing h and $p_2(c, h)$: $\mu_2(p_2(c, h), h)$
4. Guests choose where to direct their search;
5. Each host matched with a guest who was not matched before draws the cost of effort c;
6. Each host chooses whether or not to exert effort: $e_2(c, p_2(h), h)$;
7. Transactions occur.

1.2.2 Equilibrium Characterization

The equilibrium concept used is symmetric perfect Bayesian equilibrium with pure strategies in prices. In this setting, posted prices play two separate functions. First, prices "direct" guests' search behavior as they affect the number of guests who are willing to be matched with hosts. Moreover, prices posted in period 2 can be a signal for hosts' cost of effort. I limit my analysis imposing some assumptions regarding these two tasks of prices.

In line with the directed search literature, I assume that, in each period, the ex-ante guests' utility U_t cannot be affected by the price posted by a single host:

$$U_t = (a\bar{\mu}_t + b - p_t)\frac{\alpha(\theta_t)}{\theta_t}, \tag{1.2.1}$$

where $\bar{\mu}_t$ defines guests' beliefs about hosts' effort choice. Accordingly, changes in price p_t that do not affect guests' beliefs $\bar{\mu}_t$ are fully compensated by changes in tightness θ_t: if a host chooses a lower price, more guests direct their search towards her until the tightness increases and the guests' probability of transacting decreases. Equation 1.2.1 characterizes guests' beliefs about tightness levels for every price, even for those prices that are not posted in equilibrium. This approach is known in the directed search literature as the "market utility" approach (Wright et al., 2017).

In this setting, prices in period 2 can also serve as a signal for hosts' cost of effort since they can affect guests' beliefs $\bar{\mu}_t$. After a host is matched with a guest in period 1, her cost of effort is realized and it is private information. Hosts' cost of effort is relevant for guests' utility: while hosts with cost $c = 0$ always exert effort, hosts with positive cost $c = k > 0$ strategically choose whether to exert effort or not.

Yet, prices in period 2 are not the only variable signaling hosts' cost of effort. Hosts' histories are observed by guests in period 2 and they may be informative about hosts' cost. When a host's history reports $e_1 = 0$, guests in period 2 know with certainty that she has positive cost of effort (hosts with zero cost always choose to exert effort) and she does not exert effort in period 2: $\bar{\mu}_2 = 0$. Differently, histories reporting $e_1 = 1$ can sustain positive guests' beliefs about hosts' effort in period 2 ($\bar{\mu}_2 \geq \pi$).

The signaling functions of prices and histories are related. If prices fully solve the asymmetry of information between hosts and guests, histories' signal of hosts' cost of effort is ineffective. In particular, if hosts with different cost of effort have separate pricing strategies in period 2, then guests perfectly infer hosts' costs and, in equilibrium, hosts with zero cost exert effort, whereas hosts with positive cost do not exert effort. I restrict my analysis over a class of equilibria where histories provide effective signals about hosts' costs, and I denote these equilibria as *reputational equilibria*. Moreover, I assume that prices do not affect off-the-equilibrium guests' beliefs as well.[4] Before providing a formal definition of the equilibrium, I characterize hosts' decisions proceeding by backward induction.[5]

1.2.3 Hosts' Decisions: Period 2

The effort decision in period 2 is straightforward.

Lemma 1 (Effort Decision in Period 2)**.** *In equilibrium, hosts who are matched with a guest in period 2 exert effort if and only if they have zero cost of effort $c = 0$.*

Lemma 1 directly follows from the assumption that hosts with cost $c = 0$ always exert effort. Differently, hosts with cost $c = k > 0$ always exert $e_2(k) = 0$ since effort is costly for them and they cannot commit to exert positive effort since guests direct their search without knowing hosts' effort decision.

In period 2, hosts post prices to match with guests. Hosts with the same history who were matched with guests in period 1 post the same price. Hosts who were not matched with guests in period 1 post the same price as new entrants since no information pertaining their cost of effort is revealed.

In the remaining part of the analysis, I use the following notation. I denote histories that appear in equilibrium with positive probability as follows:

$$\begin{aligned} h^1 &= (e_1 = 1); \\ h^0 &= (e_1 = 0); \\ h^\emptyset &= (\emptyset). \end{aligned}$$

Superscripts denote hosts' costs. I use superscript "pool" if hosts who draw different cost of effort may play the same strategy. If hosts who have not yet drawn the cost of effort play a strategy, I use superscript "$\emptyset$". Accordingly, the same notation $h^\emptyset$ can be used to denote histories for hosts who enter in period 1 and are not matched with guests; and for hosts who enter in period 2.

Proposition 1 (Pooling in Prices in Period 2)**.** *In any reputational equilibrium, hosts who were matched with a guest in period 1 and have the same history $h = \{h^0, h^1\}$ post the same price in*

[4]In Appendix 1.9, I discuss non-reputational equilibria and I show that their existence and stability rely on further assumptions regarding model's parameters. I also provide a more detailed discussion about the guests' beliefs off-the-equilibrium path.

[5]In Appendix 1.9, I illustrate the constrained efficient allocation and I discuss the Hosios (1990) conditions that characterize the equilibrium (proposed in the main text) implementing this allocation.

period 2. Given guests' interim beliefs $\bar{\mu}_2$ and the expected utility U_2, hosts post prices $p_2^{pool}(h)$ and guests direct their search so as to form tightness $\theta_2^{pool}(h)$:

$$\alpha'(\theta_2^{pool}(h)) = \frac{U_2}{a\bar{\mu}_2(h) + b}$$
$$p_2^{pool}(h) = a\bar{\mu}_2(h) + b - \frac{\theta_2^{pool}(h)}{\alpha(\theta_2^{pool}(h))}U_2,$$

if $a\bar{\mu}_2(h) + b \geq U_2$. Otherwise, $\theta_2^{pool}(h) = 0$ and $p_2^{pool}(h) = 0$. Hosts who were not matched with a guest in period 1 and new entrants post the same price $p_2^{\emptyset}$ and guests direct their search so as to form tightness $\theta_2^{\emptyset}$:

$$\alpha'(\theta_2^{\emptyset}) = \frac{U_2}{a\bar{\mu}_2(h^{\emptyset}) + b}$$
$$p_2^{\emptyset} = a\bar{\mu}_2(h^{\emptyset}) + b - \frac{\theta_2^{\emptyset}}{\alpha(\theta_2^{\emptyset})}U_2,$$

if $b \geq U_2$. Otherwise, $\theta_2^{\emptyset} = 0$ and $p_2^{\emptyset} = 0$.

The proof of this proposition is in Appendix 1.9. Proposition 1 establishes a relationship between the price posted by hosts in period 2 and the effort exerted in period 1. If hosts do not exert effort, guests realize that they have positive cost $c = k > 0$ and they do not exert effort in period 2: $\bar{\mu}_2(h^0) = 0$. Conversely, if hosts exert effort, then guests can only partially guess their cost of effort and $\bar{\mu}_2(h^1) > \pi$. Accordingly, exerting effort in period 1 rises hosts' prices $p_2^{pool}(h)$ and the probability to have a transaction $\alpha(\theta_2^{pool}(h))$. Still, hosts with histories h^0 are matched with guests with positive probability if $b > 0$.

As shown in Equation 1.2.1, the ex-ante guests' utility of a match does not vary across hosts with different histories, or, using a directed search term, different submarkets.

This is one of the main characteristics of the directed search framework and it is key to allow for the presence of hosts active in the market with different reputation levels and prices.

Corollary 1 (Guests Directed Search in Period 2)**.** *Guests' expected utility for a match in period 2 is the same across hosts active in the market:*

$$(a\bar{\mu}_2(h^1) + b - p_2^{pool}(h^1))\frac{\alpha(\theta_2^{pool}(h^1))}{\theta_2^{pool}(h^1)} = U_2$$
$$(a\bar{\mu}_2(h^{\emptyset}) + b - p_2^{\emptyset})\frac{\alpha(\theta_2^{\emptyset})}{\theta_2^{\emptyset}} \leq U_2$$
$$(a\bar{\mu}_2(h^0) + b - p_2^{pool}(h^0))\frac{\alpha(\theta_2^{pool}(h^0))}{\theta_2^{pool}(h^0)} \leq U_2.$$

Hosts with history h^1 are always matched with guests in period 2 with positive probability. Yet, hosts with histories $h^{\emptyset}$ and h^0 may not be matched if the expected guests' gross utility from a match with these hosts is too low. If this is the case, the last two conditions in Corollary 1 do not bind.

At the beginning of period 2, hosts can enter the market paying entry costs f. Once they enter, they will charge $p_2^{\emptyset}$ according to Proposition 1. In particular, the following entry condition characterizes the expected profits of new entrants:

$$p_2^{\emptyset}\alpha(\theta_2^{\emptyset}) \leq f. \tag{1.2.2}$$

Condition 1.2.2 is binding if a positive measure of hosts enters in period 2.

1.2.4 Hosts' Decisions: Period 1

In period 1, hosts who draw a positive cost of effort $c = k > 0$ choose whether to exert effort or not. Their decision is reported in their history and it changes the expected profits in period 2 according to Proposition 1.

Proposition 2 (Effort Decision in Period 1). *In any reputational equilibrium, hosts who are matched with a guest in period 1 always exert effort if they have zero cost of effort, $c = 0$: $e_1(0) = 1$. If their cost of effort is positive, $c = k > 0$, they exert effort with probability $\omega \in [0, 1]$. ω is unique and it depends on the values of a, b, π, the cost of effort k, and the discount factor β.*

The proof of Proposition 2 is in Appendix 1.9. Directly from the effort choice by hosts with $c = k > 0$, it is possible to derive the guest's beliefs about hosts' effort in period 2.

Corollary 2 (Guests Beliefs Updating). *Guests' interim beliefs about hosts' expected effort in period 2 are formed applying Bayes formula when possible:*

$$\begin{aligned}\bar{\mu}_2(h^1) &= \frac{\pi}{\pi + (1-\pi)\omega} \\ \bar{\mu}_2(h^{\emptyset}) &= \pi \\ \bar{\mu}_2(h) &= 0, \ \forall h \neq h^1, h^{\emptyset}.\end{aligned}$$

Guests (do not) update interim beliefs observing the price posted in period 2 (in equilibrium and off-equilibrium). In particular, given a history h, $\mu_2(h, p_2)$ is equal to $\bar{\mu}_2(h)$.

In period 1, hosts have not yet drawn their cost of effort when they post prices. Accordingly, the optimal pricing in period 1 is established in a condition of symmetric information between hosts and guests. Thus, guests' beliefs about hosts' effort in period 1 are not affected by prices: $\mu_1(p_1^{\emptyset}) = \pi + (1-\pi)\omega$. The optimal pricing is uniquely derived as follows.

Proposition 3 (Pooling in Prices in Period 1). *In equilibrium, given guests' expected utility for a match U_1, hosts post prices $p_1^{\emptyset}$ and guests direct their search so as to form tightness $\theta_1^{\emptyset}$:*

$$\begin{aligned}\alpha'(\theta_1^{\emptyset}) &= \frac{U_1}{a(\pi + (1-\pi)\omega) + b - k(1-\pi)\omega + \beta\Delta\Pi} \\ p_1^{\emptyset} &= a(\pi + (1-\pi)\omega) + b - \frac{\theta_1^{\emptyset}}{\alpha(\theta_1^{\emptyset})}U_1,\end{aligned}$$

where $\Delta\Pi$ *represents the hosts' value of a transaction in terms of reputation updating. It is defined as follows:*

$$\Delta\Pi = \Pi_2(a\bar{\mu}_2(h^1)+b)(\pi+(1-\pi)\omega)+(1-\pi)(1-\omega)\Pi_2(a\bar{\mu}_2(h^0)+b)-\Pi_2(a\bar{\mu}_2(h^\emptyset)+b).$$

If $a(\pi+(1-\pi)\omega)+b-k(1-\pi)\omega+\beta\Delta\Pi < U_1$, *then* $\theta_1^\emptyset = 0$ *and* $p_1^\emptyset = 0$.

The proof of this proposition is in Appendix 1.9. Proposition 3 establishes that the value of a transaction in period 1 is not only related to the guests' expected utility ($a(\pi+(1-\pi)\omega)+b$) and the cost of effort ($k(1-\pi)\omega$), but it embeds a reputational value for hosts. If hosts draw $c = 0$, then they benefit from having a transaction since they get, with zero cost, expected profits $\Pi_2(a\bar{\mu}_2(h^1)+b)$ in period 2 with $\Pi_2(a\bar{\mu}_2(h^1)+b) \geq \Pi_2(a\bar{\mu}_2(h^\emptyset)+b)$. Conversely, if hosts draw $c = k > 0$, then having a transaction is not necessarily beneficial in terms of reputation updating. In particular, if $\omega = 0$, hosts with $c = k > 0$ get $\Pi_2(a\bar{\mu}_2(h^0)+b) \leq \Pi_2(a\bar{\mu}_2(h^\emptyset)+b)$.

In contrast with the multiple active submarkets in period 2, hosts do not show different histories in period 1. Thus, all guests direct their search to the only active submarket with expected utility U_1.

Corollary 3 (Guests Directed Search in Period 1)**.** *Guests' expected utility for a match in period 1 is defined as follows:*

$$(a(\pi+(1-\pi)\omega)+b-p_1^\emptyset)\frac{\alpha(\theta_1^\emptyset)}{\theta_1^\emptyset} = U_1.$$

Finally, at the beginning of period 1, hosts may enter the market paying entry costs f. The left-hand side of following entry condition characterizes the expected profits of entrants in period 1:

$$\begin{aligned} &(p_1^\emptyset - k(1-\pi)\omega)\alpha(\theta_1^\emptyset) \\ +&(1-\pi)(1-\omega)\beta\alpha(\theta_1^\emptyset)p_2^{pool}(h^0)\alpha(\theta_2^{pool}(h^0)) \\ +&(\pi+(1-\pi)\omega)\beta\alpha(\theta_1^\emptyset)p_2^{pool}(h^1)\alpha(\theta_2^{pool}(h^1)) \\ &+\beta(1-\alpha(\theta_1^\emptyset))p_2^\emptyset\alpha(\theta_2^\emptyset) \leq f. \end{aligned} \tag{1.2.3}$$

Condition 1.2.3 is binding if a positive measure of hosts enters in period 1.

In the remainder of this Section, I provide a formal definition of reputational equilibria and I analyze their existence and uniqueness.

Definition 1 (Reputational Equilibrium)**.** *A Reputational Equilibrium is defined by the following elements for period 1 and period 2, respectively:*

- $n_1, p_1, \mu_1(p_1), U_1, e_1(c, p_1)$: *the number of hosts who enter the market, the pricing decision, the guest' beliefs about hosts' effort, the guests' expected utility for a match, and the effort decision by hosts with cost of effort* $c = 0$ *and* $c = k > 0$ *in period 1, respectively;*

- $n_2(h), g_2(h, p_2(c,h)), p_2(c,h), \bar{\mu}_2(h), \mu_2(h, p_2(c,h)), U_2, e_2(c, p_2(c,h))$: *the number of hosts with history h present in the market, the number of guests who direct the search to hosts with certain history and price, the hosts' pricing decision for each cost and history, the guests' interim and updated beliefs about hosts' effort, the guests' expected utility for a match in period 2, and the effort decision by hosts with cost of effort $c = 0$ and $c = k > 0$ in period 2, respectively.*

The following conditions are satisfied in equilibrium:

1. *The market tightness in period 1 is defined as $\theta_1^{\emptyset} = \frac{1}{n_1}$;*
2. *The measures of hosts with history h^1 and h^0 in period 2 depend on the measure of hosts who entered in period 1, the probability of hosts drawing $c = 0$, π, and the probability to exert effort by hosts with $c = k > 0$, ω:*

$$n_2(h^1) = (\omega(1-\pi) + \pi)\alpha(\theta_1^{\emptyset})n_1$$
$$n_2(h^0) = (1-\omega)(1-\pi)\alpha(\theta_1^{\emptyset})n_1;$$

3. *Guests in period 2 are assigned to different sets of hosts characterized by the couple formed by history and price. Tightness levels are such that $\theta_2(h) = \frac{g_2(h, p_2^{pool}(h))}{n_2(h)}$ and:*

$$\sum_h g_2(h, p_2^{pool}(h)) = G;$$

4. *The free-entry conditions 1.2.2 and 1.2.3 do not allow positive profits for hosts who enter the market in both periods;*
5. *Hosts post prices according to Propositions 1 and 3;*
6. *Guests' beliefs about hosts' effort in period 1 are $\mu_1(p) = \pi + (1-\pi)\omega$; whereas guests' beliefs in period 2 are formed according to Corollary 2;*
7. *Guests' expected utility levels from a match are defined according to Corollaries 1 and 3;*
8. *Hosts exert effort depending on their cost of effort according to Proposition 2 and Lemma 1.*

After having defined the equilibrium, I proceed with the theorem regarding its existence and uniqueness.

Theorem 1 (Existence and Uniqueness with Entry)**.** *If the measure of guests active in period 2 is greater than a threshold value $\bar{G}$, then reputational equilibrium exists and it is unique. In this equilibrium, a positive mass of hosts enters in both periods.*

The proof of Theorem 1 is in Appendix 1.9.

1.2.5 Testable Predictions

Here I propose the main prediction of the model that can be directly tested using data from Airbnb. It follows from the comparison of two reputational equilibria with different entry costs for hosts.

Proposition 4 (Entry Costs and Effort)**.** *Consider two reputational equilibria in which the entry costs are f and f' with $f' > f$, and the measure of guests present in the market in period 2 is big enough to allow hosts' entry in both periods for f and f'. Then, in the reputational equilibrium associated with f', the probability that hosts with cost of effort $c = k > 0$ exert effort in period 1 is weakly higher than in the reputational equilibrium associated with f.*

Here I provide a heuristic proof for the proposition above.[6] If entry costs increase, the number of hosts who enter the market in period 2 decreases. The market is now tighter for guests in period 2 and guests' expected utility U_2 decreases. Conversely, hosts' expected profits increase and they increase more for hosts with better reputation. This is obvious if $b = 0$ and guests never direct their search to hosts with history h^0 in period 2. In this case, independently of the entry costs, hosts' expected profits in period 2 are zero if h^0. Conversely, the profits increase if hosts have histories h^1 or $h^\emptyset$. Thus, in period 1, hosts who draw $c = k > 0$ have stronger incentives to exert effort since the benefits of exerting effort - having a better reputation in period 2 - are higher. Accordingly, since more hosts with $c = k$ exert effort in period 1, the beliefs to have $c = 0$ with history h^1 drop. This leads to a lower premium of having good reputation.

The heuristics of the proof relies on the positive relationship between the tightness of the market is period 2 and the incentives to exert effort in period 1. In line with this mechanism, the empirical results in Section 1.5 address the effect of a change in competition, due to a variation in entry costs, over the effort exerted by hosts on Airbnb. The identification strategy described in Section 1.4 proposes an instrumental variable that follows the channel highlighted in the proof of Proposition 4. Hosts anticipate the movement in tightness due to an exogenous change in entry costs. Thus, comparing hosts located in different areas, hosts exert more effort where the number of competitors drops more significantly: in a less competitive framework, exerting effort leads to greater reputational benefits. In Section 1.6, two additional predictions are tested. They directly follow from the same comparative statics exercise of Proposition 4 and they can be tested using the same variations in entry cost.

Corollary 4 (Entry Costs, Profits and the Value of Reputation)**.** *Consider two reputational equilibria in which the entry costs are f and f' with $f' > f$, and the measure of guests present in the market in period 2 is big enough to allow hosts' entry in both periods for f and f'. Then, in the reputational equilibrium associated with f':*

1. *Hosts' profits in period 2 are higher relative to the reputational equilibrium associated with f;*

2. *The value of reputation in period 2, that is the premium for having history h^1 is lower relative to the reputational equilibrium associated with f.*

[6] The interested reader may find the complete proof in Appendix 1.9.

1.3 Empirical Setting and Dataset

In this Section, I introduce the empirical part of my work. First, I present the Airbnb setting. Then, I describe the regulation for short-term rentals in the city of San Francisco and I focus on the settlement agreement signed in May 2017 by the San Francisco City Council and Airbnb. Finally, I describe the unique dataset used for my analysis: I provide descriptive statistics about the population of Airbnb listings before and after the agreement signed in May 2017.

1.3.1 Airbnb

Airbnb is one of the leading digital platforms in the hospitality industry. It operates in more than 60,000 cities and it offers its members the possibility to arrange and offer lodging and other tourism experiences. Airbnb receives a commission fee for every transaction and it does not own any real estate listed on the platform. I restrict my analysis to lodging services and I denote the Airbnb members who arrange and offer accommodations as guests and hosts, respectively. To be an Airbnb member, a digital registration procedure is required. Airbnb guests need to provide personal information such as the email, and a phone number. The procedure to become an Airbnb host is different. It requires hosts to provide additional information and take photos of the listing; choose the days when they are willing to host; and set prices.[7] Further requirements are necessary for hosts due to local laws and regulations.

After being registered, guests and hosts appear on the Airbnb platform with a personal webpage. Guests can search for hosts that match the location and the period of their stay. Furthermore, other advanced filters are available to restrict the guests' search, such as price range and listings' characteristics. Guests can select hosts and visit their webpages. Then, they can choose to book the listing. If hosts accept guests' requests, their listings are officially booked.

After the guest's stay, host and guest have 14 days to review each other. Guests feedback consists of four elements:

1. A written comment;
2. Private comments to the host;
3. A one-to-five star rating about the overall experience;
4. Six specific ratings regarding the following categories:
   - The accuracy of the listing description;
   - The check-in process at the beginning of the stay;
   - The cleanliness of the listing;
   - The communicativeness of the host;

[7]For more information regarding the registration procedure for Airbnb hosts, see the official Airbnb guide to becoming a host at www.airbnb.com/b/hosting_checklist.

  - The listing location;
  - The "value-for-money" of the stay.

Similarly, a host can review guests answering whether or not she would recommend the guest; writing a comment; and rating the guest considering the communicativeness, the cleanliness and how well the guest respected the rules of the house. Not all these elements are published on the platform and, for what concerns the guest feedback, only written comments are directly published on hosts' webpages. Ratings are not displayed singularly with the comments: only the rounded average of the score and subscores are published on the listing and the host webpages. In the same way, only the comment written by the host is published on the guest webpage.

1.3.2 Institutional Setting

Airbnb and other online marketplaces have had a sizable impact on the hospitality industry and many city councils have tried to regulate rentals on digital platforms. The identification strategy proposed in this paper exploits a change in regulation effective in San Francisco that lead many Airbnb listings to exit the platform in few months. To have a better sense of impact of such a policy, I report here a synthetic chronology of the regulations adopted by the San Francisco City Council starting from the San Francisco Short-Term Rentals Regulation enacted in February 2015.

The San Francisco Short-Term Rentals Regulation (February 2015)

With an ordinance signed in October 2014 and effective from February 2015, the San Francisco city council legalized short-term rentals in the city. Before this ordinance, San Francisco banned short rentals in residential buildings. Rentals are considered "short-term" if the properties are rented for less than 30 consecutive nights at a time. Short-term rentals constitute the great majority of transactions occurring on hospitality digital platforms. Still, listings present on Airbnb can be exempt from the registration requirements if they only accept guests for periods of 30 or more days; or in case they are professional structures such as hotels and B&B. The regulation is mainly composed of the following parts:[8]

- Only San Francisco permanent residents who own or rent single-family dwellings in the city are eligible to engage in short-term rentals. In particular, hosts must reside in their dwellings for at least 275 days per year;

- Resident tenants must notify their landlords before engaging in short-term rentals;[9]

[8]For a comprehensive analysis of all the regulation's requirements, see the Short-Term Residential Rental Starter Kit provided by the San Francisco Office of Short-Term Rental at https://businessportal.sfgov.org/start/starter-kits/short-term-rental, and the official text of the ordinance at https://sfgov.legistar.com/View.

[9]If the contract between tenant and landlord prohibits subletting, the landlord may evict the tenant. Moreover, tenants cannot charge more rent than they are paying to the landlord and rent control laws must be respected.

- Only the primary residence can be used for short-term rentals;
- When a host is absent, the dwelling can be rented for a maximum of 90 days per year;
- Hosts must obtain a permit and register at the Office of Short-Term Rental. Every two years, they must pay a $250 fee. Moreover, hosts are required to obtain a city business license;
- The San Francisco hotel tax must be collected from renters and paid to the cityFor Airbnb hosts, the platform automatically collects and pays such a tax for its hosts;
- Hosts must be covered by an insurance with a coverage of at least $500,000. Airbnb provides hosts with 1 million in coverage. Compliance to city building code requirements is necessary.

This regulation introduces several limitations on who can offer lodging service on Airbnb. To be legally present on the platform, hosts have to face additional costs and respect extra requirements.

In the first years after the introduction of the regulation, the enforcement of part of the law had proven to be difficult. In particular, regulators could not enforce the rules regarding hosts residence since registration rates at the Office of Short-Term Rental were very low and digital platforms did not disclose to the authorities any personal information regarding their hosts. Because of the difficulties regarding the enforcement of the law, San Francisco city council enacted an additional ordinance in June 2016 that required digital platforms to list on their websites only legal listings with official registration. Airbnb filed a suit against the City Council and, after a U.S. judge rejected the suit and postponed the enforcement of the new rules, an agreement was found in May 2017.

The Settlement Agreement with Airbnb (May 2017)

The agreement clarifies the role of digital platforms in the hosts registration process for short-term rentals. It has been signed, together with the San Francisco City Council, by Airbnb and another hospitality platform, HomeAway. The main resolutions are the following:[10]

- From September 2017, new hosts willing to arrange a short-term rental on Airbnb or HomeAway have to "input their city Office of Short-Term Rental registration number (or application pending status) to post a listing";
- From September 2017, a "pass-through registration" system is implemented by Airbnb and HomeAway for hosts who are already registered on the platforms to send applications directly to the Office of Short-Term Rental for consideration. If the platforms receive notice of an invalid registration, they will cancel future stays and deactivate the listings;

[10] All quotes are from the official announcement of the San Francisco City Attorney, available at https://www.sfcityattorney.org.

- From January 2018, all hosts present on Airbnb and HomeAway are required to be registered. If some listings are not registered at this date, the platform will cancel future stays and deactivate the listings until a registration number (or application pending status) is provided.

1.3.3 InsideAirbnb Dataset

The dataset for this study comes from information on InsideAirbnb, a website that tracks all the Airbnb listings present in specific locations over time.[11] In my analysis, the dataset is formed by forty-seven snapshots of all the Airbnb listings present in San Francisco at forty-seven different dates from May 2015 to July 2019. Data scraping is performed at the beginning of each month with some months missing in 2015 and some multiple snapshots per month at the beginning of 2018.[12] I combine all the snapshots to form an unbalanced panel dataset composed of 30,266 listings and 350,099 listing observations over time. In each snapshot, listings are observed if they appear on the Airbnb website at the snapshot date. Accordingly, for each Airbnb listing in the dataset, entry, exit, and inactivity periods are identified.[13] When a listing is observed, several listing characteristics are displayed. Some are time-invariant such as the listing's location (longitude, latitude and neighborhood), and dwelling's characteristics. Some others update at each snapshot such as the number of guests' reviews and average star ratings, the price charged for one night at the snapshot date, the number of nights in which the listing is available after the snapshot, whether or not the listing displays the Office of Short-Term Rental registration number and whether the registration is necessary for the listing.

Descriptive statistics are reported in Table 1.1. Panel A presents the characteristics of all listings observed in the panel data from May 2015 to July 2019. All the reported variables correspond to the last snapshot in which listings are observed. The average amount of time that listings are present on Airbnb is approximately one year. The total number of reviews has a skewed distribution with more than half of listings having less than 5 reviews before exiting the platform. There is high variability in the price per night and the number of nights in which the listing is available after the snapshot, implying that performances on Airbnb widely vary across listings. In contrast, the variation of the average rating is much lower. The percentages regarding the number of hosts engaging in short-term rentals and displaying a registration number confirm two elements highlighted in the previous Section regarding Airbnb in San Francisco. First, short-term rentals constitute the great majority of transactions occurring

[11] All data are publicly available on InsideAirbnb. InsideAirbnb is "an independent, non-commercial set of tools and data that allows you to explore how Airbnb is really being used in cities around the world" and all scraped data are available under a Creative Commons CC0 1.0 Universal (CC0 1.0) license.

[12] The list of all snapshots follows: May 2015, September 2015, November 2015, December 2015, February 2016, April 2016, May 2016, June 2016, July 2016, August 2016, September 2016, October 2016, November 2016, December 2016, January 2017, February 2017, March 2017, April 2017, May 2017, June 2017, July 2017, August 2017, September 2017, October 2017, November 2017 (two snapshots), December 2017 (two snapshots), January 2018 (two snapshots), February 2018, March 2018, April 2018, May 2018, July 2018, August 2018, September 2018, October 2018, December 2018, January 2019, February 2019, March 019, April 2019, May 2019, June 2019, July 2019.

[13] Airbnb hosts can decide to remove their listings from Airbnb for a period of time and then re-enter with the same listing profile.

on Airbnb (more than 80 percent). Second, before the Settlement Agreement, the regulation imposed by the San Francisco City Council was largely ignored. Panel B shows listings information regarding the number of reviews written between two consecutive snapshots and the averages of the ratings associated to these reviews. All the variables are constructed starting from the original variables shown in Panel A. I call these variables, the number of reviews per snapshot and the average ratings per snapshot. The number of reviews per snapshot is derived from the difference between the total number of reviews displayed in a snapshot and in the next one ($n_{i,t+1} - n_{i,t}$). Similarly, the average ratings per snapshot are computed using the average rating and the total number of reviews. I denote with $n_{i,t}$ and $\bar{R}^k_{i,t}$ the total number of reviews displayed for listing i at snapshot t and the average rating displayed for listing i at snapshot t for the category k, respectively. Then, the average rating per snapshot, $\bar{r}^k_{i,t}$, for listing i at snapshot t and category k where $k \in \{$*overall, accuracy, check-in, cleanliness, communication, location, value*$\}$ can be computed as follows:[14]

$$\bar{r}^k_{i,t} = \frac{\bar{R}^k_{i,t+1} n_{i,t+1} - \bar{R}^k_{i,t} n_{i,t}}{n_{i,t+1} - n_{i,t}}.$$

The number of reviews per snapshot varies by listing and snapshot. The average number of review per snapshot equals 1.5 with standard deviation 2.8. Much more limited variations are present for the average ratings per snapshot. The averages are higher than 9 for all the ratings with standard deviations always lower than 1.2. The average rating regarding the overall experience is 93.9 with standard deviation 9.2, that corresponds to an average of almost 5 stars with an extremely limited variation.[15] This result is in line with Zervas et al. (2015) who observe that almost 95 percent of Airbnb listings have an average rating greater or equal than 4.5 stars.

1.3.4 The Settlement Agreement: Exit, Entry, and Hosts' Selection

The Short-Term Rental Regulation has been effective since February 2015. However, as highlighted in Section 1.3.2, the enforcement of listings' registration at San Francisco Office of Short-Term Rental has proven to be difficult. The Settlement Agreement, effective from September 2017, addressed the enforcement difficulties of registration. It implemented a resolution that forced every eligible Airbnb listings to be registered before January 2018. Figure 1.1 reports the percentage of Airbnb listings offering short-term lodging that displayed a registration number at each snapshot. Before September 2017, less than 15 percent of listings displays a registration number. Conversely, at the beginning of 2018, when the Settlement Agreement has been completely implemented, the percentage of listings offering short-term lodging with registration numbers reaches 100 percent and it stays constant afterwards.

[14]Since $\bar{R}^k_{i,t}$ are rounded averages, the procedure is likely to be affected by measurement errors. In order to reduce these errors, I drop the observations corresponding with values of $\bar{r}^k_{i,t}$ lower than 0 or greater than 10. For each rating, these values account for less than 2 percent of the sample. Moreover, I drop observations about snapshots with a number of reviews per snapshot greater than 26. I treat these snapshots as outliers due to the scraping method. They account for 0.08 percent of the sample.

[15]On the Airbnb platform guests can choose in a range of stars between 1 and 5. Still, the scraped variable regarding the average rating for the overall experience varies from 0 to 100. All other scraped ratings varies from 0 to 10.

Table 1.1: Summary Statistics

	Mean	SD	N	Min	Max
Panel A					
Days in Airbnb	382.5	417.9	30,266.0	0.0	1,526.0
Total number of reviews	21.6	49.0	30,266.0	0.0	724.0
Percent of the listing population:					
Less than 5 reviews	58%	-	30,266.0	-	-
Between 5 and 10 reviews	9%	-	30,266.0	-	-
Between 10 and 20 reviews	10%	-	30,266.0	-	-
Between 20 and 50 reviews	11%	-	30,266.0	-	-
Between 50 and 100 reviews	6%	-	30,266.0	-	-
More than 100 reviews	6%	-	30,266.0	-	-
Short-term rentals	81%	-	30,266.0	-	-
Registration displayed or not required	42%	-	30,266.0	-	-
Price per night	206.8	189.2	30,009.0	0.0	1,500.0
Availability next 30 days	8.9	11.0	30,266.0	0.0	30.0
Availability next 60 days	20.1	22.3	30,266.0	0.0	60.0
Availability next 90 days	34.7	33.9	30,266.0	0.0	90.0
Minimum nights required	8.3	13.2	30,266.0	1.0	100.0
Panel B					
Average rating: overall	93.9	9.2	20,987.0	20.0	100.00
Number of reviews per snapshot	1.5	2.8	24,834.0	0.0	26.0
Average rating per snapshot: overall	93.3	8.8	14,849.0	0.0	100.0
Average rating per snapshot: accuracy	9.5	0.9	14,840.0	0.0	10.0
Average rating per snapshot: check-in	9.7	0.8	14,829.0	0.0	10.0
Average rating per snapshot: cleanliness	9.3	1.1	14,844.0	0.0	10.0
Average rating per snapshot: communication	9.6	0.8	14,840.0	0.0	10.0
Average rating per snapshot: location	9.4	0.9	14,828.0	0.0	10.0
Average rating per snapshot: value	9.1	1.0	14,827.0	0.0	10.0

Note: Panel A refers to every single listing present in the panel data combining the snapshots from May 2015 to July 2019. All the statistics refer to the last snapshot in which the listing is observed. The variable "Days in Airbnb" is derived considering the difference between the last and the first snapshot in which the listing is observed. The "Percent of the listing population" groups listings by the number of reviews that are displayed in their last snapshot. The variable "Price per night" presents the nominal prices charged by guests measured in US dollars. I drop few outliers reporting prices higher than $1500. They account for 0.65 percent of the sample. Panel B refers to the variables constructed from the original dataset about the number of reviews written between two consecutive snapshots and the averages of the ratings associated to these reviews. Missing data regarding the variables "Average rating" are due to the high presence of listings with no reviews.

Figures 1.2 and A.1 capture the change in the total number of Airbnb listings in San Francisco at each snapshot. Figure 1.2 shows the evolution of the number of Airbnb listings offering short-term lodging: from September 2016 until September 2017 the number of short-term listings remains constant between 8,000 and 9,000 units; then, when the "pass-through registration" system started to be at place, the number of listings sharply drops to 4,000 units in February 2018, when all eligible Airbnb units have to be registered. The number of short-term listings stays constant for the next months when the implementation of Settlement Agreement has been completed. To visualize the drop in the number of listings for different areas of San Francisco after the Settlement Agreement, Figures 1.3 and 1.4 present two maps with the location of Airbnb listings offering short-term lodging in San Francisco in September 2017 and in January 2018.

The evolution of the number of Airbnb listings that do *not* offer short-term lodging (from now on, long-term) is displayed in Figure A.1. The number of long-term listings, which are exempt from the regulation, steadily grows during the months in which the "pass-through registration" system starts to be implemented. Then, in August 2018, the number jumps from less than 1,000 units to more than 2,500 units in August 2018 and it continues to grow with more listings entering the platform without offering short-term lodging at the end of 2018 and at the beginning of 2019. Accordingly, the Settlement Agreement determined a selection in the type of listings that continued to be present on the platform after the implementation of the registration requirements.

I devote the rest of this Section to the study of the profile of Airbnb listings who stay on the platform after the Settlement Agreement. This is of particular importance for the identification design I propose in the next Section. I estimate the impact over the hosts' effort decisions by studying only Airbnb listings who stayed after the Settlement. This is necessary to disentangle variations in hosts' effort due to change in competition, to those due to the end-of-life concerns. The number of competitors may not be relevant for Airbnb hosts who are going to exit the market and milk the reputation.

A further motivation to study the selection of Airbnb hosts regards the changes in the composition of close competitors. This is relevant for the identification of the effect of variations in the number of competitors: the Settlement Agreement does not only reduce the number of competitors, but it also changes the composition of the close competitors for each Airbnb host.

I disentangle the effect of the drop in the number of competitors to the change in the composition in Section 1.7 by controlling for a rich set of variables describing the set of close competitors.

In Table 1.2, I present some summary statistics to characterize this selection process. Listings are divided into four groups: Group A contains all listings that exit the platform before September 2017, when the implementation of the Settlement Agreement had not started yet. Group B contains all listings that enter the platform after September 2017. Listings in Group C enter the platform before September 2017 and exit after January 2018, when the implementation of the Settlement Agreement was completed. Finally, Group D contains all listings that enter the platform before September 2017 and exit between September 2017 and January 2018. Accordingly, only listings belonging to Group C are present on Airbnb before and after the Settlement Agreement, and I restrict my attention to this set of listings in the next Sections.

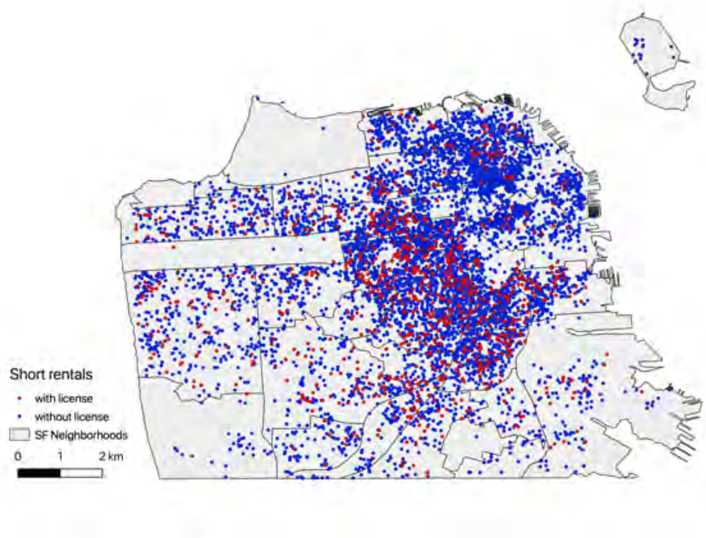
In Table 1.2, Panel A compares listings that are not affected by the Settlement Agreement (Group A) with listings that enter after September 2017 (Group B). This latter group of listings tends to engage in significantly longer rentals relative to Group A. In particular, hosts in Group B require guests to stay and rent their house for at least 15 consecutive nights, on average; whereas hosts in Group A require, on average, less than 4 consecutive nights. Accordingly, listings that enter after the Settlement Agreement are much less likely to engage in short-term rentals than those listings that are active before September 2017. The difference in the duration of the lodging services across groups may explain other differentials in terms of prices and the total number of reviews. The price per night charged by listings in Group A is significantly higher than the one charged by listings in Group B: shorter rentals tend to be more expensive. In addition, longer stays mechanically produce a lower stream of reviews over time. Moreover, listings in Group B tend to have significantly higher ratings than listings in Group A: this may be due to the different service duration, or to an improvement in the service quality provided by hosts.

A similar differential in the listing profiles is present in Panel B where listings that are present on Airbnb before and after the Settlement Agreement (Group C) are compared with those that enter before September 2017 and exit during the implementation of the new regulation (Group D). Stayers require guests to rent for more consecutive nights relative to listings in Group D and they charge lower prices. Still, they have a greater turnover since the number of reviews per snapshot is higher for Group C than Group D. Moreover, listings that stay after January 2018 have significantly higher ratings relative to those that exit before. In this sense, listings in Group C seem to be selected among those that present on Airbnb before the Settlement Agreement.

In Table A.1, I show statistics measured in September 2017 for listings in Groups C and D. In September 2017, listings in Group C have, on average, almost five times more reviews than in Group D, and enter the platform almost thirty days before. Listings in Group C charge significantly lower prices than listings in Group D and have higher ratings.

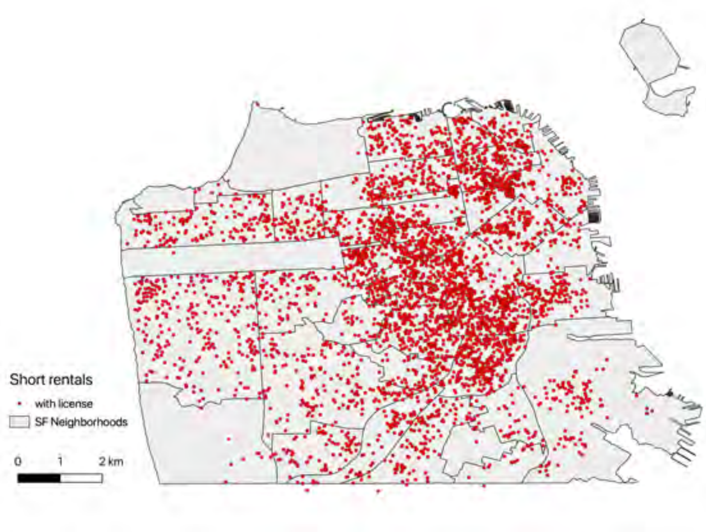
Accordingly, other than reducing the number of listings present on the platform, the regulation enforcement of the Settlement Agreement may have affected hosts' effort through the selection of hosts who stay after the enforcement of the registration. In order to tackle this issue, in Section 1.5, I restrict my analysis to those listings that enter before September 2017 and exit after January 2018, when the registration enforcement is completed (Group C). Still, external validity concerns may be at place restricting the sample on those listings that survive the registration enforcement. The estimated effects of competition over hosts' effort are based on a selected part of the population. However, the main purpose of this study is not to evaluate the policy and all its effects on the San Francisco hospitality market. Here, I study a specific effect of the Settlement Agreement on a restricted part of the Airbnb population in order to shed new lights on the process of reputation building and its relationship with variations in the number of competitors.

Figure 1.3: Location of Airbnb Short-Term Listings in San Francisco: September 2017



Note: The map shows the location of all Airbnb listings offering short-term lodging in San Francisco that were present for the snapshot associated with September 2017. Blue dots correspond to generic short-term Airbnb listings; whereas red dots correspond to listings that display a registration number.

Figure 1.4: Location of Airbnb Short-Term Listings in San Francisco: January 2018



Note: The map shows the location of all Airbnb listings offering short-term lodging in San Francisco that were present for the snapshot associated with January 2018. Red dots correspond to generic (registered) short-term Airbnb listings.

Table 1.2: Summary Statistics: the Settlement Agreement and Listings Selection

	Group A		Group B			
	Mean	SD	Mean	SD	Δ	$p-value$
Panel A						
Days in Airbnb	158.4	192.8	177.6	143.8	-19.2	0.0
Total number of reviews	11.0	24.8	7.5	16.7	3.5	0.0
Price per night	200.6	185.6	196.2	175.3	4.3	0.1
Availability next 30 days	11.1	11.5	8.9	10.9	2.2	0.0
Average rating per snapshot: overall	91.3	10.4	95.0	9.03	-3.6	0.0
Average rating per snapshot: accuracy	9.3	1.1	9.7	0.82	-0.3	0.0
Average rating per snapshot: check-in	9.5	0.9	9.8	0.78	-0.3	0.0
Average rating per snapshot: cleanliness	9.1	1.3	9.5	1.11	-0.4	0.0
Average rating per snapshot: communication	9.5	1.0	9.7	0.80	-0.2	0.0
Average rating per snapshot: location	9.3	1.1	9.6	0.8	-0.3	0.0
Average rating per snapshot: value-for-money	8.9	1.2	9.2	1.1	-0.3	0.0
Minimum nights required	3.8	7.2	19.0	17.8	-15.2	0.0
Short-term rentals	96%	-	45%	-	-0.5	-
Registration displayed or not required	34%	-	49%	-	-0.1	-
Number of listings	12,896	-	6,533	-	-	-

	Group C		Group D			
	Mean	SD	Mean	SD	Δ	$p-value$
Panel B						
Days in Airbnb	1,056.5	383.8	571.4	244.1	485.1	0.0
Total number of reviews	71.6	87.8	11.5	26.6	60.1	0.0
Price per night	207.5	177.0	244.0	230.7	-36.5	0.0
Availability next 30 days	7.02	9.7	4.9	9.7	2.1	0.0
Average rating per snapshot: overall	94.2	6.3	92.8	9.1	1.4	0.0
Average rating per snapshot: accuracy	9.6	0.7	9.5	1.0	0.2	0.0
Average rating per snapshot: check-in	9.8	0.5	9.7	0.8	0.1	0.0
Average rating per snapshot: cleanliness	9.5	0.8	9.2	1.2	0.3	0.0
Average rating per snapshot: communication	9.8	0.6	9.7	0.8	0.1	0.0
Average rating per snapshot: location	9.5	0.7	9.4	1.0	0.1	0.0
Average rating per snapshot: value-for-money	9.2	0.8	9.1	1.0	0.1	0.0
Minimum nights required	10.8	14.7	3.2	4.7	7.6	0.0
Short-term rentals	73%	-	99%	-	0.3	-
Registration displayed or not required	73%	-	5%		0.7	-
Number of listings	5,418	-	3,992	-	-	-

Note: The two panels compare the profile of listings before and after the Settlement Agreement. All variables refer to the last snapshot in which the listing is observed apart from the variables "Average rating per snapshot". Listings are divided in four groups: Group A includes all listings that exit the platform before September 2017. Group B includes all listings that enter the platform after September 2017. Group C includes all listings that enter the platform before September 2017 and exit after January 2018. Group D includes all listings hat enter the platform before September 2017 and exit before January 2018. The last two columns provide the differences between the averages of relevant characteristics and the $p-value$ of the difference.

1.4 Identification Strategy

In this Section I discuss the identification strategy of the causal relationship between listing competition in Airbnb and the hosts' effort supporting the main prediction in Section 1.2. The model shows that variations in the entry costs change market tightness (the proportion of guests and hosts) affecting hosts' incentives to exert effort. In particular, if entry costs increase, hosts exert effort with higher probability to have better reputation in the future. The identification design closely follows the same channel: the variation in competition is due to the change in entry conditions established by the Settlement Agreement. The effect of this regulation on listing concentration varies across areas in San Francisco and the empirical strategy exploits these differences with a shock-based instrumental variable (IV) design.

The main estimating regression to capture the causal impact of competition on hosts' effort is the following:

$$\bar{r}_{i,t}^{effort} = \alpha_i + \rho_t + \beta \ln(L_{i,t}^j) + \varepsilon_{i,t}, \tag{1.4.1}$$

where α_i and ρ_t are the full set of dummy variables for each listing i and snapshot t. $\bar{r}_{i,t}^{effort}$ is a measure of hosts' effort. I use two rating categories as proxies for hosts' effort: check-in and communication. From now on, I denote the average rating per snapshot for listing i, snapshot t and category check-in and communication with $\bar{r}_{i,t}^{check}$ and $\bar{r}_{i,t}^{comm}$, respectively. I use $\bar{r}_{i,t}^{effort}$ to simultaneously refer to both average ratings. The focus on these two categories is justified by a principal component analysis performed on all the rating categories (average rating per snapshot). In Appendix 1.11, Figure A.3 plots the loadings of all categories over the only two components with eigenvalues greater than one (see Figure A.2). Check-in and communication are the most correlated ratings and their loadings separate from all others. In Section 1.6, I provide an estimation of the effort exerted by hosts using a control function approach to account for reviews' confounding factors related to guests' characteristics.

$L_{i,t}^j$ represents the degree of competition faced by listing i at snapshot t. It is defined as the sum of all listings offering short-term lodging at snapshot t within j kilometers of listing i. In my analysis I use three values for j: 0.5 kilometer, 1 kilometer, and 2 kilometers.[16] I use a logarithmic specification for the variable $L_{i,t}^j$ to facilitate the interpretation of coefficient β as a semi-elasticity: it expresses the impact of one percentage change in the number of listings over the ratings regarding effort.

With ordinary least squares (OLS), the correlation between $L_{i,t}^j$ and $\varepsilon_{i,t}$ produces inconsistent estimates of β. The main potential threat of endogeneity is with regard of the presence of omitted variables concerning the demand side. A high number of competitors is a signal of the attractiveness of the area and high demand. Thus, regressing $\bar{r}_{i,t}^{effort}$ over $\ln(L_{i,t}^j)$ may partially capture the impact of changes in demand over hosts' effort.

To tackle the endogeneity issues related to unobserved variations in the demand, I implement an IV strategy exploiting the Settlement Agreement between the San Francisco City Council and Airbnb. Accordingly, I restrict my analysis to listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 (Group C in Section 1.3.4).

[16]These variables are created using information regarding latitude and longitude of each listing.

In the same spirit as Dafny et al. (2012), Ashenfelter et al. (2015), and Chandra and Weinberg (2018), I propose a measure γ_i^j of the *predicted* change in the sum of listings within j kilometers of listing i due to the registration enforcement. The measure γ_i^j is the percentage of listings offering short-term lodging within j kilometers of listing i that display a registration number on their webpages few days before the Settlement Agreement became effective.[17] It is defined as follows:

$$\gamma_i^j = \frac{RL_{i,Sept2017}^j}{L_{i,Sept2017}^j},$$

where $RL_{i,Sept2017}^j$ and $L_{i,Sept2017}^j$ are the sum of listings offering short-term lodging with registration numbers and the total sum of listings offering short-term lodging, respectively, present at the beginning of September 2017 and within j kilometers of listing i.[18] A value of γ_i^j close to 1 implies that the competition for listing i offering short-term lodging is not expected to change much since a high number of listings already displays a license. Conversely, low values of γ_i^j imply that the expected change in competition for listing i due to the Settlement Agreement is likely to be more relevant. Figure A.4 shows the distribution of γ_i^1 for the set of listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018: the values of γ_i^1 span from 0 (less than 0.1 percent) to 0.5; more than 80 percent of listings has at least 10 percent of registered competitors within 1 kilometer ($\gamma_i^1 > 0.1$).

The instrumental variable is formed by the product between γ_i^j and $post_{Nov2017}$: a dummy variable that takes value 1 for each snapshot after November 2017 and is zero otherwise.[19]

The power and the validity of this instrument depends on the strong correlation between γ_i^j and $L_{i,t}^j$ and on the assumption about monotonicity and the exclusion restriction. The "first stage" of the IV design documents a positive and significant relationship between the actual movement of the number of competitors for each listing and how the registration enforcement was expected to change the degree of competition.

The estimating equation of the "first stage" is the following:

$$\ln(L_{i,t}^j) = \alpha_i + \rho_t + \beta\gamma_i^j \times post_{Nov2017} + \varepsilon_{i,t} \tag{1.4.2}$$

where the endogenous variable $\ln(L_{i,t}^j)$ is regressed over the expected change in competition due to the Settlement Agreement. Results with listings and snapshot fixed effects are in Table 1.3 reporting standard errors clustered by listing (Columns (1), (2), and (3)) and adjusted to account for spatial dependence as in Conley (1999) (Columns (4), (5), and (6)).[20] The expected movement in the number of competitors, γ_i^j, is a good predictor for the actual change in competition occurring after November 2017: the higher is the value of γ_i^j , the lower is the expected negative effect of the Settlement Agreement over the hosts' population surrounding

[17]The snapshot in September 2017 was scrapped on September 2, 2017, whereas the new registration process started September 6, 2017. See http://www.sfexaminer.com/airbnb-launches-new-registration-system/.

[18]If listing i is not active on the platform on September 2017, I compute the measure γ_i^j using the month in which listing i is active before September 2017 and as close as possible to this date.

[19]From Figure 1.2, November 2017 results to be the first snapshot with a significant drop in the number of listings offering short-term lodging in the platform.

[20]To compute Conley (1999) standard errors I use the method suggested by Colella et al. (2019).

listing i (in line with the monotonicity assumption). For each distance, all coefficients are positive and significant with a F-statistics much above the standard threshold to detect the presence of weak instruments. Accounting for spatial dependence reduces the size of the F-statistics in line with the fact that listings located in the same area tend to have highly correlated values of $\ln(L^j_{i,t})$ and γ^j_i. In Table A.2, standard errors clustered by neighborhood and robust standard errors are reported to show the robustness of the first-stage results to the choice about standard errors. The magnitudes of the effects depends on the radius used to determine the set of competitors. In particular, the coefficients are greater for larger radii. This is partially mechanical since the number of competitors varies with the radius, whereas the range for the proportion of registered listings is always from 0 to 1.

To show further evidence of the predictive power of γ^j_i relative to the number of competitors for listing i over time, I illustrate the evolution of $L^j_{i,t}$ for different values of γ^j_i, and I integrate it with an event-study approach. I divide the population of Airbnb listings using the associated value of γ^1_i (the proportion of registered listings in September 2017 within 1 kilometer of listing i). In particular, I select those listings with a value of γ^1_i lower or equal than the 33th percentile of the distribution ($\gamma^1_i \leq 0.12$); and those with a value greater or equal than the 66th percentile of the distribution ($\gamma^1_i \geq 0.16$). Figure 1.5 shows the average values of $\ln(L^j_{i,t})$ over time for these two groups. The solid line depicts the evolution of the number of competitors for those listings that are predicted to be the most affected by the Settlement Agreement because of the low values of γ^1_i. Conversely, the dotted line shows the average value of $\ln(L^j_{i,t})$ for those listings that are predicted to be the least affected by the Settlement Agreement (high values of γ^1_i). From Figure 1.5 it is possible to observe that the drop of listing after the registration enforcement is much greater for the solid line relative to the dotted one, confirming the assumption that γ^1_i can predict the variation in the number of competitors surrounding each listing due to the Settlement Agreement.

I complement this analysis showing to which extent the dynamics in the number of competitors of each listing can be predicted by γ^j_i. I consider the following lead-lag model in which the degree of competition $L^j_{i,t}$ is regressed over the product between γ^j_i and a full set of dummy variables for each snapshot from September 2016 (one year before the registration enforcement started to be implemented) until January 2019 (one year after the end of the enforcement implementation):

$$\ln(L^j_{i,t}) = \alpha_i + \rho_t + \sum_{\tau=Sept2016}^{Jan2019} \beta_\tau \gamma^j_i \times 1(t=\tau) + \varepsilon_{i,t}. \tag{1.4.3}$$

I present the results of the OLS estimates of Equation 1.4.3 with an event study graph. I plot the estimated β_τ over the snapshot dates using the number of competitors within 1 kilometer in Figure 1.6. Before September 2017, the coefficients are close to zero and they do not exhibit a clear trend: this evidence shows that the evolution of Airbnb listings before the Settlement Agreement is not correlated with γ^j_i. Conversely, the number of listings after September 2017 is positively correlated with γ^j_i: the number of listings offering short-term lodging sharply decreases after the Settlement Agreement (as it shown in Figure 1.2) and Airbnb listings are more likely to stay if the value of γ^j_i (the proportion of registered listings before the implementation of the Settlement Agreement) is higher.

With regard to the exclusion restriction, there is a list of arguments to support the assumption that the instrument ($\gamma_i^j \times post_{Nov2017}$) does not directly affect the dependent variable $\bar{r}_{i,t}^{effort}$, and it does only through its impact on the number of listings. There is no evidence that the San Francisco Short-Term Rental Regulation and the Settlement Agreement were motivated by policymakers' concerns over the quality of the services on hospitality platforms.[21]

To account for the selection of hosts who stay after the enforcement of the registration, I restrict my analysis to those listings that enter before September 2017 and exit after January 2018, when the registration enforcement is completed (Group C in Section 1.3.4). For this sample, the identification strategy excludes the presence of unobserved factors that affect hosts' effort and that are correlated with the predicted variations in the number of listings for different areas of San Francisco.

Figures 1.5 and 1.6 present supportive evidence for this assumption: in Figure 1.5, the evolution of $\ln(L_{i,t}^j)$ for listings with different values of γ_i^j shows parallel trends before the Settlement Agreement. In line with this finding, Figure 1.6 shows that the estimated β_τ associated with the months before September 2017 are close to zero and no trend is detected. Accordingly, all evidence suggests that the instrumental variable is not correlated with unobservables affecting the evolution of the number of competitors.

In order to provide similar evidence regarding the correlation between the instrumental variable and unobservables affecting hosts' effort, I illustrate in Figures A.5 and A.6 the evolution of hosts' effort for different values of γ_i^j, in line with the analysis of Figure 1.5. These figures show the ratings of those listings that are more affected by the Settlement Agreement increase more relative to those who are less affected. To make this argument more rigorous, I conduct the second event-study analysis. I consider a lead-lag model in which the ratings regarding effort $\bar{r}_{i,t}^{effort}$ are regressed over the product between γ_i^j and a full set of dummy variables for each snapshot:

$$\bar{r}_{i,t}^{effort} = \alpha_i + \rho_t + \sum_{\tau=Sept2016}^{Jan2019} \beta_\tau \gamma_i^j \times 1(t=\tau) + \varepsilon_{i,t}. \tag{1.4.4}$$

As in the previous event-study, I present the results of the OLS estimates of Equation 1.4.4 with an event study graph. In Figures 1.7 and A.7, I plot the estimated β_τ over the snapshot dates considering the ratings regarding check-in and communication, respectively.

In both figures, the coefficients related to the months before September 2017 do not exhibit trends; whereas a negative trend is observable after the Settlement Agreement. These pieces of evidence are in line with the exclusion restriction assumption: unobservables affecting ratings regarding hosts' effort do not correlate with the instrumental variable before the registration enforcement. Furthermore, the negative trend after September 2017 supports the prediction of the model: when hosts face more competition (for higher values of γ_i^j), their incentives to exert effort decrease.

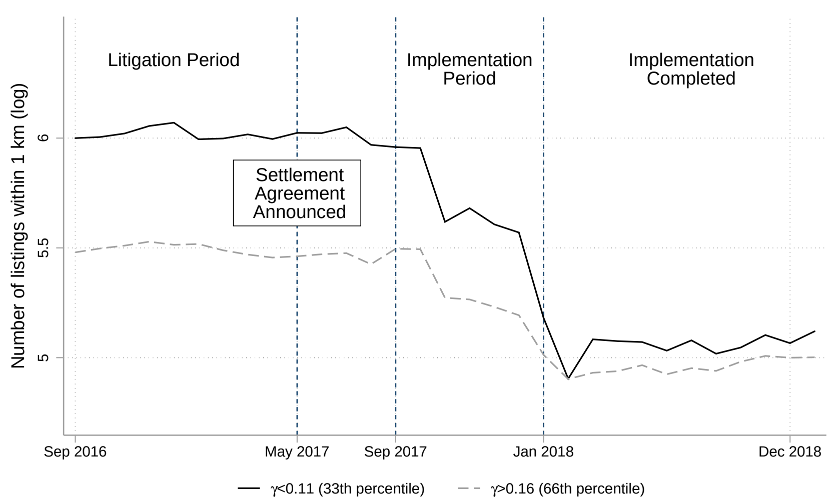
[21]The City Attorney, Dennis J. Herrera, never mentions the quality of the Airbnb service and the hosts' effort in his announcement of the Settlement Agreement, available at https://www.sfcityattorney.org.

Table 1.3: Impact of the Settlement Agreement on Competition (First Stage)

	$\ln(L^{0.5}_{i,t})$ (1)	$\ln(L^{1}_{i,t})$ (2)	$\ln(L^{2}_{i,t})$ (3)	$\ln(L^{0.5}_{i,t})$ (4)	$\ln(L^{1}_{i,t})$ (5)	$\ln(L^{2}_{i,t})$ (6)
$\gamma_i^{0.5} \times post_{Nov2017}$	1.497***			1.497***		
	[0.0819]			[0.129]		
$\gamma_i^{1} \times post_{Nov2017}$		2.477***			2.477***	
		[0.0804]			[0.219]	
$\gamma_i^{2} \times post_{Nov2017}$			3.222***			3.222***
			[0.0443]			[0.267]
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	4.227	5.488	6.737	4.227	5.488	6.737
F-test	663.3	1467.9	4023.8	133.6	126.9	144.6
R^2	0.0998	0.106	0.120	0.0998	0.106	0.120
N	57,323	57,330	57,344	57,323	57,330	57,344

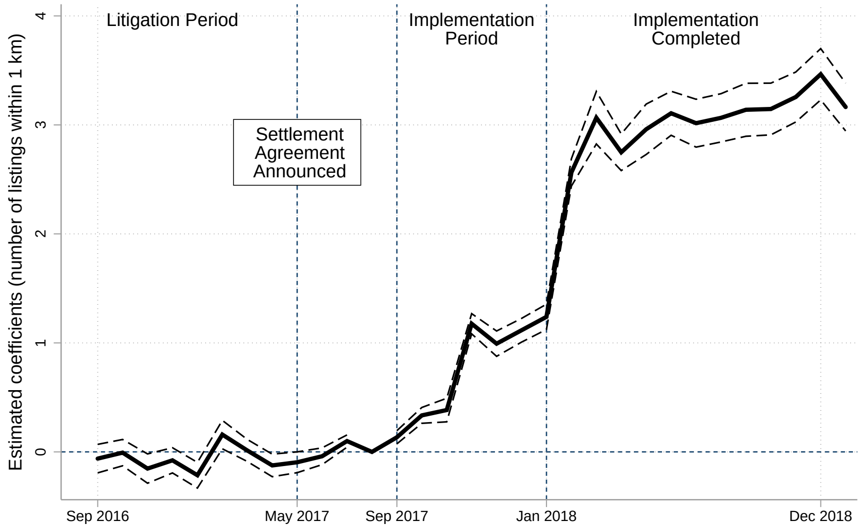
Note: Only listings offering short-term lodging that enter before September 2017 and exit after January 2018 are considered. In Columns (1), (2), and (3) standard errors clustered by listing are in parentheses. In Columns (4), (5), and (6) standard errors (in parentheses) are adjusted to reflect spatial autocorrelation as in Conley (1999). The autocorrelation is assumed to linearly decrease up to a cutoff of 10 km (covering all territory of San Francisco). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 1.5: Evolution of $\ln(L^{1}_{i,t})$ for Different Groups of Listings



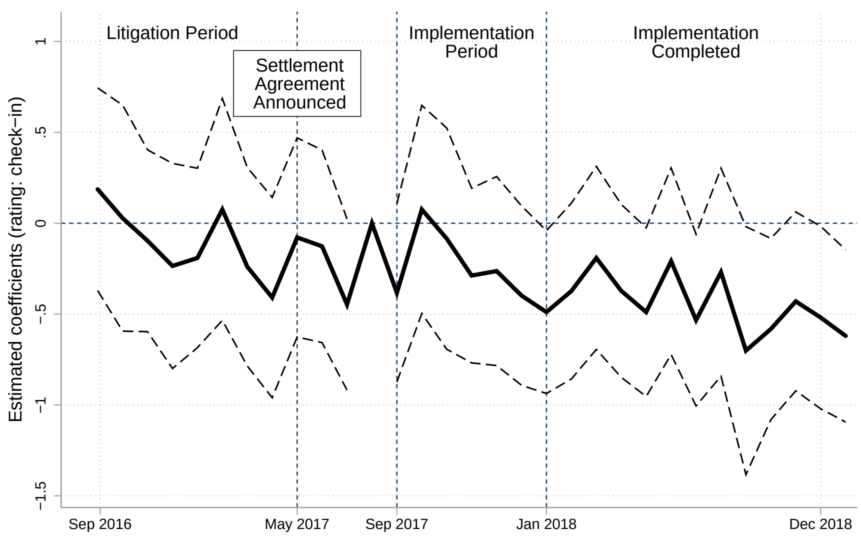
Note: The figure plots the average values of $\ln(L^{j}_{i,t})$ for different groups of listings. The solid line represents $\ln(L^{j}_{i,t})$ for those listings with $\gamma_i^1 \leq 0.12$; whereas the dotted line represents the $\ln(L^{j}_{i,t})$ for those listings with $\gamma_i^1 \geq 0.16$. Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. Listings represented by the solid line are predicted to be the most affected by the Settlement Agreement; whereas listings represented by the dotted line are predicted to be the least affected.

Figure 1.6: Estimated Coefficients from Equation 1.4.3: Number of Listings within 1 km



Note: In line with Equation 1.4.3, $\ln(L^1_{i,t})$ is regressed on listing and snapshot fixed effects, and on the products between γ^1_i and snapshot dummies. Standard errors are clustered by listing. The graph plots the estimated coefficients on these products. The value of the coefficient corresponding to August 2017 ($\hat{\beta}_{Aug2017}$) is normalized to zero. Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered.

Figure 1.7: Estimated Coefficients from Equation 1.4.4: Ratings Regarding Check-in



Note: In line with Equation 1.4.4, $\bar{r}^{check-in}_{i,t}$ is regressed on listing and snapshot fixed effects, and on the products between γ^1_i and snapshot dummies. Standard errors are clustered by listing. The graph plots the estimated coefficients on these products. The value of the coefficient corresponding to August 2017 ($\hat{\beta}_{Aug2017}$) is normalized to zero. Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered.

1.5 Main Results

I now present the main empirical results. To facilitate the comparison across different regressions, I always restrict my analysis to Airbnb listings that offer short-term lodging; enter the platform before September 2017; exit after January 2018; without missing data regarding the variables $\bar{r}_{i,t}^{check-in}$ and $\bar{r}_{i,t}^{comm}$. I consider data starting from September 2016 (one year before the registration enforcement started to be implemented) to January 2019 (one year after the end of the implementation). Throughout the next Sections, I allow the variance of residuals to differ across listings by clustering standard errors at listing level.[22] I start by estimating the OLS panel regressions that relate hosts' effort to the degree of competition, as represented in Equation 1.4.1. Table 1.4 presents the results. For each rating, three regressions are performed: the independent variables vary depending on the distance used to delimit the competition faced by listings. The results suggest a not significant negative relationship between effort and competition measured as the sum of competitors within 0.5, 1 and 2 kilometers to each listing. Tables A.3, A.4, and A.5 present the same results with standard errors accounting for Conley (1999) spatial correlation, clustered by neighborhood, and using the heteroskedasticity robust specification, respectively. When standard errors are not clustered (Tables A.3 and A.5), the coefficients for the relationship between $\bar{r}_{i,t}^{check-in}$ and the sum of competitors within 1 and 2 kilometers becomes statistically significant at 10 and 5 percent, respectively.

As described in Section 1.4, the OLS panel regressions are likely to be affected by the presence of omitted determinants of demand: the higher is the number of Airbnb hosts in a specific area, the greater is the area attractiveness for guests. Because of this, causality cannot be inferred from the OLS panel model. Accordingly, I take advantage of the variation in the degree of competition due to the Settlement Agreement to estimate the effect of competition over hosts' effort.

Table 1.3 shows the statistical and economic significance of γ_i^j in predicting the number of competitors faced by each listing after November 2017 (the "first stage"). In particular, when γ_i^j increases by 0.1 percent, the number of competitors within 0.5 kilometers increases by more than 15 percent, those within 1 kilometer by more than 24 percent, and those within 2 kilometers by almost 33 percent. The difference in the magnitudes of the parameters is partially mechanical. Values of γ_i^j range between 0 and 1, whereas the number of listings increases with the radius considered. Before presenting the results regarding the IV estimates, I show the effect of the expected change in competition due to the regulation (the instrument) on the hosts' ratings about effort. The estimating equation presents the same functional form as Equation 1.4.2:

$$\bar{r}_{i,t}^{effort} = \alpha_i + \rho_t + \beta\gamma_i^j \times post_{Nov2017} + \varepsilon_{i,t} \tag{1.5.1}$$

[22] I present standard errors that allow for correlations among competitor listings in line with Conley (1999) (in Appendix). It is tempting to consider geographically wider cluster levels, such as neighborhood. Yet, only thirty-six neighborhoods are present in San Francisco. Results with clustered standard errors at neighborhood level and heteroskedasticity robust standard errors are shown in Appendix.

Table 1.4: OLS Estimates of the Impact of Competition on Hosts' Effort

	$\bar{r}_{i,t}^{check-in}$			$\bar{r}_{i,t}^{comm}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(L_{i,t}^{0.5})$	-0.0077			-0.0016		
	[0.012]			[0.011]		
$\ln(L_{i,t}^{1})$		-0.022			-0.013	
		[0.016]			[0.016]	
$\ln(L_{i,t}^{2})$			-0.036			-0.010
			[0.022]			[0.022]
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	9.900	9.900	9.900	9.879	9.879	9.879
R^2	0.0055	0.0042	0.0024	0.0058	0.0049	0.0043
N	57,323	57,330	57,344	57,323	57,330	57,344

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. Standard errors clustered by listing are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.5: Impact of the Settlement Agreement on Hosts' Effort (Reduced Form)

	$\bar{r}_{i,t}^{check-in}$			$\bar{r}_{i,t}^{comm}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\gamma_i^{0.5} \times post_{Nov2017}$	-0.183***			-0.159***		
	[0.0646]			[0.0608]		
$\gamma_i^{1} \times post_{Nov2017}$		-0.272***			-0.267***	
		[0.0960]			[0.0872]	
$\gamma_i^{2} \times post_{Nov2017}$			-0.316***			-0.259**
			[0.115]			[0.102]
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	9.900	9.900	9.900	9.879	9.879	9.879
R^2	0.0023	0.0018	0.0020	0.0028	0.0022	0.0030
N	57,323	57,330	57,344	57,323	57,330	57,344

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. Standard errors clustered by listing are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.6: IV Estimates of the Impact of Competition on Hosts' Effort

	$\bar{r}_{i,t}^{check-in}$			$\bar{r}_{i,t}^{comm}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(L_{i,t}^{0.5})$	-0.122***			-0.106**		
	[0.0438]			[0.0412]		
$\ln(L_{i,t}^{1})$		-0.110***			-0.108***	
		[0.0389]			[0.0354]	
$\ln(L_{i,t}^{2})$			-0.0982***			-0.0804**
			[0.0357]			[0.0318]
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	9.900	9.900	9.900	9.879	9.879	9.879
R^2	0.0022	0.0011	0.00062	0.0024	0.00068	0.00017
N	57,323	57,330	57,344	57,323	57,330	57,344

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. Standard errors clustered by listing are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

This equation constitutes the "reduced form" of the IV estimates. Alternatively, it can be interpreted as a difference-in-difference design with a continuous control (the variable γ_i^j) that defines the extent to which the listing is affected by the regulation, i.e. the listing propensity to be treated by the shock. Table 1.5 presents the results using standard errors clustered by listing. Tables A.6, A.7, A.8 present the same results with standard errors accounting for Conley (1999) spatial correlation, clustered by neighborhood, and using the heteroskedasticity robust specification, respectively. For every specification and every rating, a negative and significant relationship between the instrument $\gamma_i^j \times post_{Nov2017}$ and hosts' effort is observed. Accordingly, lower values of γ_i^j, that predict a greater drop in the number of competitors for each listing, are associated with higher hosts' effort after November 2017. In this sense, a lower number of competitors is beneficial for hosts' ratings about effort. The parameters are also economically significant: when $\gamma_i^{0.5}$ changes from 0 to 1, $\bar{r}_{i,t}^{check-in}$ and $\bar{r}_{i,t}^{comm}$ decrease by almost 2 percent. Drops by more than 3 percent are associated with longer distances γ_i^1 and γ_i^2. It is important to note that the distributions of $\bar{r}_{i,t}^{effort}$ (presented in Table 1.2 for listings in Group C) are extremely concentrated and the magnitude of these changes roughly accounts for two third of standard deviation.

Finally, I turn to the IV estimates. $\ln(L_{i,t}^j)$ is the only endogenous variable in Equation 1.4.1, and only one instrumental variable is derived to predict the impact of the regulation, $\gamma_i^j \times post_{Nov2017}$. Then, the two-stage least squares parameters correspond to the ratio between the coefficients derived before for the "reduced form" and the "first stage" regressions (Equations 1.5.1 and 1.4.2, respectively).

The estimates are in Table 1.6 using standard errors clustered by listing. Tables A.9, A.10, A.11 present the same results with standard errors accounting for Conley (1999) spatial correlation, clustered by neighborhood, and using the heteroskedasticity robust specification, respectively. The results show a significant and negative effect of the number of competitors over hosts' effort in line with the parameters of the reduced form. The negative and significant impact of the IV almost double the OLS estimates where the confounding factors due to demand side lead to inconclusive results. Moreover, the negative impact of the competition over hosts' effort is in line with the main prediction of the model (Proposition 4). In a less competitive setting, reputation concerns become more relevant and hosts exert effort with higher probability. In particular, a 10 percent decrease in the number of competitors leads to a increase of around 0.01 star for the ratings $\bar{r}_{i,t}^{check-in}$ and $\bar{r}_{i,t}^{comm}$. As commented before, the distributions of $\bar{r}_{i,t}^{effort}$ are very concentrated and a one-star change accounts for more than one standard deviation.

Interestingly, the magnitude of the parameters monotonically decreases with the distance; the lowest parameters for both ratings are associated with a distance of 2 kilometers. This result may suggest that listings located in the same area are likely to exert a greater competitive pressure relative to those further away.

1.6 Extensions

In this Section, I present evidence supporting the other theoretical predictions proposed in Section 1.2 (Corollary 4). First, I show a negative causal relationship between the number of competitors and hosts' profits. To do so, I exploit the Settlement Agreement as exclusion restriction following the same empirical design explained in Section 1.4. Then, I analyze the monetary value of reputation and how it is affected by the change in competition due to the Settlement Agreement. My findings are in line with Elfenbein et al. (2015): they show that, in eBay, competition significantly increases the monetary value of reputation for eBay seller. Finally, I present evidence regarding the impact of the Settlement Agreement on Airbnb listings offering no short-term lodging services: a few months after the full implementation of the registration restriction, more than two thousand listings started to offer no short-term rentals. As a response to such variation, I observe that Airbnb hosts not offering short-term lodging decrease effort. This result confirms again the model's predictions: in Section 1.5, I study the relationship between effort and competition when the number of competitors decrease; whereas here I consider a positive shock in competition.

1.6.1 Competition and Profits

According to the model in Section 1.2, when the number of competitors decreases, hosts are more likely to exert effort and their expected profits to increase. Without information about the hosts' costs it is not possible to recover hosts' profits. Yet, I observe for each listing i and snapshot t the price charged per night, $p_{i,t}$, and the number of available nights to rent in the next 30 days, $available_{i,t}^{30}$. With these two variables, it is possible to compute a proxy regarding hosts' profits, $\pi^{30}_{i,t}$, as follows:[23]

$$\pi^{30}_{i,t} = p_{i,t}(30 - available^{30}_{i,t}).$$

I use the variable $\pi^{30}_{i,t}$ to study the relationship between profits and the number of competitors. The identification of the causal relationship follows the same strategy used for the ratings regarding hosts' effort. Accordingly, I conduct an event-study analysis to provide evidence about the correlation between the instrumental variable and unobservables affecting $\pi^{30}_{i,t}$. I consider a lead-lag model in which $\pi^{30}_{i,t}$ is regressed over the product between γ^j_i (the percentage of registered listings in September 2017 offering short-term lodging within j kilometers of listing i) and a full set of dummy variables for each snapshot:

$$\pi^{30}_{i,t} = \alpha_i + \rho_t + \sum_{\tau=Sept2016}^{Jan2019} \beta_\tau \gamma^j_i \times 1(t=\tau) + \varepsilon_{i,t}. \tag{1.6.1}$$

In Figure A.8 , I plot the estimated β_τ of Equation 1.6.1 over the snapshot dates. The coefficients related to the months before September 2017 do not exhibit trends (although the full set of dummy has not completely removed some seasonality effects). Conversely, the coefficients after January 2018 slightly decrease relative to the values before the Settlement Agreement. This is in line with the exclusion restriction assumption: unobservables affecting profits do not correlate with the instrument variable before the registration restriction's announcement. Furthermore, the negative trend after September 2017 shows that, hosts' revenues decrease when hosts face more competition, captured by higher values of γ^j_i. Similarly to the previous analysis regarding host's effort, I show the effect of the instrument $\gamma^j_i \times post_{Nov2017}$ on $\pi^{30}_{i,t}$, that is the "reduced form" of the IV estimates. The estimating equation is the following:

$$\pi^{30}_{i,t} = \alpha_i + \rho_t + \beta\gamma^j_i \times post_{Nov2017} + \varepsilon_{i,t}. \tag{1.6.2}$$

Table 1.7 presents the results. The coefficients regarding $\gamma^{0.5}_i$ and γ^1_i show a negative and significant impact of the proportion of registered listings before the Settlement Agreement over hosts' revenues. Conversely, the coefficient of γ^2_i is negative, but not significant. The effect is also economically relevant. When $\gamma^{0.5}_i$ varies from 0 to 1, hosts' monthly profits decrease by more than 400 US dollars after November 2017. Similarly, if γ^1_i varies from 0 to 1, hosts' monthly profits decrease by more than 700 US dollars after November 2017. This findings support the model predictions. As before, the two-stage least squares coefficients are equal to the ratio between the parameters derived of the "reduced form" and the "first stage" regressions (Equations 1.6.2 and 1.4.2, respectively). Thus, the IV estimates provide the same result regarding the relationship between competition and profits. The estimates are in Table 1.8. The results show a significant and negative effect of the number of competitors within 0.5 and 1 kilometers over hosts' profits, whereas the the number of competitors within 2 have a negative, but not significant impact. The effect is also economically relevant: a 10 percent decrease in the number of competitors within 0.5 kilometer leads to a increase of more than 30 US dollars, that is almost 1%, in the monthly profits by hosts.

[23]Measurement errors may affect this proxy variable. In particular, hosts may not be available to rent in some days for external reasons and not because the dwellings are already booked. Accordingly, the proxy may overestimate the total host's profits.

Table 1.7: Impact of the Settlement Agreement on Hosts' Profits (Reduced Form)

	$\pi_{i,t}^{30}$	$\pi_{i,t}^{30}$	$\pi_{i,t}^{30}$
$\gamma_i^{0.5} \times post_{Nov2017}$	-453.3*		
	[247.2]		
$\gamma_i^{1} \times post_{Nov2017}$		-909.3**	
		[412.7]	
$\gamma_i^{2} \times post_{Nov2017}$			-603.9
			[988.0]
Listing FE	✓	✓	✓
Snap FE	✓	✓	✓
Mean	3806.1	3805.8	3805.4
R^2	0.018	0.018	0.018
N	57,319	57,326	57,340

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. Standard errors clustered by listing are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.8: IV Estimates of the Impact of Competition on Hosts' Profits

	$\pi_{i,t}^{30}$	$\pi_{i,t}^{30}$	$\pi_{i,t}^{30}$
$\ln(L_{i,t}^{0.5})$	-302.9*		
	[165.2]		
$\ln(L_{i,t}^{1})$		-367.2**	
		[166.6]	
$\ln(L_{i,t}^{2})$			-187.4
			[306.7]
Listing FE	✓	✓	✓
Snap FE	✓	✓	✓
Mean	3806.1	3805.8	3805.4
R^2	0.0076	0.0059	0.011
N	57,319	57,326	57,340

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. Standard errors clustered by listing are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

1.6.2 Competition and the Value of Reputation

The main prediction of the model regards the impact of competition on the reputational incentives to exert effort. In particular, I show that competition may erode the power of reputation to discipline users' behavior. In the previous Section, I report convincing evidence regarding Airbnb hosts' behavior in line with this prediction. However, using the same theoretical mechanism, it is possible to predict the effect on the economic value of having good reputation.

As it is pointed out in Section 1.2, the effect of having a history showing positive effort (good reputation) over the future expected profits depends on the proportion of hosts having such a history. If all hosts have good reputation, then histories lose their signaling power since guests cannot use them to update their beliefs about hosts' future effort decision. Conversely, when a smaller fraction of the hosts have a good reputation, then histories are signals of hosts' quality and they positively affect hosts' profits in the future. Accordingly, since the hosts' probability of exerting effort decreases with a higher degree of competition, it is possible to argue that the higher is the competition, the greater is the value of having good reputation.

This is in line with the findings by Elfenbein et al. (2015) observed using eBay data. They study the effect of quality certification (depending on users' ratings) on the probability to sell an item for eBay sellers. Their results show that the positive effect of certification is higher in more competitive settings and when certification is scarce.

Here I provide evidence supporting this prediction using Airbnb data. I use a hedonic regression approach in line with the literature that studies the value of reputation in online platforms (Cabral and Hortaçsu, 2010; Fan et al. (2016); Jolivet et al., 2016). Yet, I exploit the exogenous change in competition due to the Settlement Agreement to analyze how variations in the number of competitors affect the monetary value of reputation. To do this, I consider the following equation:

$$\pi_{i,t}^{30} = \alpha_i + \rho_t + \beta_1 \bar{R}_{i,t}^{effort} + \beta_2 \gamma_i^j \times post_{Nov2017} + \beta_3 \bar{R}_{i,t}^{effort} \times \gamma_i^j \times post_{Nov2017} + \varepsilon_{i,t}, \quad (1.6.3)$$

where $\pi_{i,t}$ is the proxy variable for hosts' profit defined above; and $\bar{R}_{i,t}^{effort}$ represents the average ratings regarding check-in and communication displayed for listing i at snapshot t. $\bar{R}_{i,t}^{effort}$ are the ratings displayed on the platform and, as they are averages, their variations over time are slower than (but in line with) the variations on the average ratings per snapshots $\bar{r}_{i,t}^{effort}$ that were analyzed in the previous Sections. Substituting $\bar{R}_{i,t}^{effort}$ with $\bar{r}_{i,t}^{effort}$ does not qualitatively alter the results of this Section.

The coefficient β_1 captures the relationship between the ratings displayed for listing i and its profits in the following thirty days. According to the mechanism presented above, more competitive settings should strengthen this relationship. To study this effect of competition, I multiply $\bar{R}_{i,t}^{effort}$ with the product $\gamma_i^j \times post_{Nov2017}$ that has a great predictive power over the changes in the number of competitors after the Settlement Agreement (see Section 1.4). In particular, higher values of γ_i^j predict a greater number of competitors staying in the market (since they have already complied with the regulation). In line with the model prediction, a greater amount of competitors should magnify the positive relationship between $\bar{R}_{i,t}^{effort}$ and $\pi_{i,t}$ resulting in a positive value for the coefficient β_3.

Results are in Table 1.9 for ratings regarding check-in and communication and for different distances. They support the prediction of a positive and significant impact of competition on the value of reputation ($\beta_3 > 0$). In particular, the effect of one-star increase in the average rating regarding check-in $\bar{R}_{i,t}^{check-in}$ over hosts' profit increases by more than $1,500$ US dollars if γ_i^j changes from 0 to 1. Similarly, the effect of one-star increase in the average rating regarding communication $\bar{R}_{i,t}^{comm}$ over hosts' profit increases by more than 600 US dollars if γ_i^j changes from 0 to 1.

1.6.3 Long-Term Listings and the Settlement Agreement

The Settlement Agreement has a profound impact on the enforcement of the Short-Term Rentals Regulation and, as a direct result, on the number of Airbnb listings offering short-term lodging active in San Francisco. However, it also has an indirect effect on the number of listings that do *not* rent short-term, but are present on the platform.

As shown in Figure A.1, the number of Airbnb listings that do not rent short-term (long-term) steadily grows from September 2017 to January 2018 and, after few months from the full implementation, the number jumps with an increase of more than two thousand units in August 2018.

The following regression provides convincing evidence that the massive entry in the market of long-term rentals is mainly due to hosts that could not comply with the Short-Term Rentals Regulation and exited the platform few months before. Entrants have new identification numbers and it is not possible to directly claim that they have already entered (and exited) the platform in previous periods. Yet, γ_i^j, the proportion of registered short-term listings in September 2017, has a significant predictive power over the variations of Airbnb long-term listings after the Settlement Agreement.

To observe this, I can repeat the "first stage" regression of the IV design with the following equation:

$$\ln(LL_{i,t}^j) = \alpha_i + \rho_t + \beta\gamma_i^j \times post_{Aug2018} + \varepsilon_{i,t} \tag{1.6.4}$$

where the endogenous variable $\ln(LL_{i,t}^j)$ represents the logarithm of the sum of all listings offering long-term lodging at snapshot t within j kilometers of listing i.

The dummy variable $post_{Aug2018}$ takes value 1 for each snapshot after August 2018 and it is zero otherwise.[24] I restrict my analysis on listings offering long-term lodging that enter the platform before September 2017 and exit after January 2018. This is the same period used for the previous analysis regarding short-term rentals. This restriction is necessary to remove the potential effect of selection on the estimates.

Results with listings and snapshot fixed effects are in Table 1.10 and they confirm that the expected movement in the number of competitors, γ_i^j , is a good predictor for the change in competition occurring after August 2018. Results with listings and snapshot fixed effects are in Table 1.10 and they confirm that the expected movement in the number of competitors, γ_i^j , is a good predictor for the change in competition occurring after August 2018.

[24]From Figure A.1, August 2018 results to be the first snapshot with a significant jump in the number of listings offering long-term lodging in the platform.

Table 1.9: Impact of the Settlement Agreement on the Value of Reputation

	$\pi^{30}_{i,t}$			$\pi^{30}_{i,t}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\gamma_i^{0.5} \times post_{Nov2017}$	-15,941.6***			-6,820.6*		
	[4,740.3]			[3,787.6]		
$\gamma_i^{1} \times post_{Nov2017}$		-20,014.4***			-8,118.1*	
		[5,231.5]			[4,255.3]	
$\gamma_i^{2} \times post_{Nov2017}$			-19,566.4***			-8,130.0*
			[5,116.3]			[4,208.1]
$\bar{R}^{check-in}_{i,t} \times \gamma_i^{0.5} \times post_{Nov2017}$	1,553.3***					
	[476.9]					
$\bar{R}^{check-in}_{i,t} \times \gamma_i^{1} \times post_{Nov2017}$		1,914.5***				
		[516.2]				
$\bar{R}^{check-in}_{i,t} \times \gamma_i^{2} \times post_{Nov2017}$			1,898.3***			
			[553.3]			
$\bar{R}^{comm}_{i,t} \times \gamma_i^{0.5} \times post_{Nov2017}$				639.9*		
				[383.0]		
$\bar{R}^{comm}_{i,t} \times \gamma_i^{1} \times post_{Nov2017}$					724.1*	
					[417.0]	
$\bar{R}^{comm}_{i,t} \times \gamma_i^{2} \times post_{Nov2017}$						755.6
						[473.8]
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	3,805.8	3,805.5	3,805.2	3,805.8	3,805.5	3,805.2
R2	0.066	0.066	0.066	0.066	0.066	0.066
N	57,323	57,330	57,344	57,323	57,330	57,344

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. Standard errors clustered by listing are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The lower is the value of γ_i^j, the higher is the amount of listings that are likely to exit the market and, potentially, enter again offering long-term lodging. Thus, higher values of γ_i^j predict a negative effect of the Settlement Agreement over the hosts' population (renting long-term) surrounding listing i after August 2018. For each distance, all coefficients are negative and significant. As before, the F-statistics is above the standard threshold to detect weak instruments. Accordingly, Airbnb listings that rent long-term receive a positive shock in the number of competitors due to the Settlement Agreement; and this shock can be predicted using the same proportion γ_i^j used in the previous analysis.

In addition, the exogeneity of γ_i^j seems reasonable since the registration restriction did not directly affect long-term Airbnb listings. Therefore, it is possible to use this opposite shock in the number of competitors to test again the main prediction of the model. In this case, the increase in the number of competitors should have a negative impact on the hosts' incentives to exert effort.

Table 1.11 shows the results of the IV estimates regarding the impact of $\ln(LL_{i,t}^j)$ on $\bar{r}_{i,t}^{effort}$ for listings offering no short-term lodging. In line with the previous findings, the results confirm a negative effect of the number of competitors over hosts' effort. I restrict my analysis over listings that do not rent short-term and that were already present on the platform before the Settlement Agreement. This restriction is necessary to avoid selection effects that may be at work after the regulation enforcement. Still, it also bring the focus on a small sample of listings reducing the significance of the parameters. All coefficients are negative and their magnitude is similar to one presented in Table 1.6 relative to short-term listings. Yet, only three out of six coefficients are statistically significant. In particular, the coefficients regarding the $\ln(LL_{i,t}^2)$ are the most significant and negative.

Table 1.10: Impact of the Settlement Agreement on Competition for Long-term Rentals (First Stage)

	$\ln(LL_{i,t}^{0.5})$	$\ln(LL_{i,t}^1)$	$\ln(LL_{i,t}^2)$
$\gamma_i^{0.5} \times post_{Aug2018}$	-3.211***		
	[0.396]		
$\gamma_i^1 \times post_{Aug2018}$		-4.114***	
		[0.345]	
$\gamma_i^2 \times post_{Aug2018}$			-4.021***
			[0.173]
Listing FE	✓	✓	✓
Snap FE	✓	✓	✓
Mean	2.755	3.953	5.179
F-test	91.34	309.6	1,404.3
R^2	0.53	0.56	0.60
N	3,326	3,408	3,411

Note: Only listings offering long-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. Standard errors clustered by listing are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.11: IV Estimates of the Impact of Competition on Hosts' Effort for Long-term Rentals

	$\bar{r}^{check-in}_{i,t}$			$\bar{r}^{comm}_{i,t}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(LL^{0.5}_{i,t})$	-0.114			-0.201*		
	[0.0774]			[0.116]		
$\ln(LL^{1}_{i,t})$		-0.112			-0.164	
		[0.0777]			[0.106]	
$\ln(LL^{2}_{i,t})$			-0.169*			-0.239*
			[0.0896]			[0.128]
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	9.814	9.816	9.816	9.816	9.815	9.815
R^2	0.0033	0.0007	0.0005	0.0017	0.00004	0.0007
N	3,326	3,408	3,411	3,326	3,408	3,411

Note: Only listings offering long-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. Standard errors clustered by listing are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

1.7 Robustness Checks

Here I examine the robustness of the IV estimates presented in Section 1.5. This Section consists of two parts. In the first part, I provide an estimation of hosts' effort and I show the negative impact of the competition on the estimated hosts' effort. In the second part, I repeat the analysis of Section 1.5 controlling for potential changes in the composition of competition around each listing.

1.7.1 Effort Estimation

Submitting reviews, guests answer several questions about their stay. Many dimensions of the lodging service are part of the guests' feedback, and not all regards the effort exerted by hosts during the stay. In Section 1.4, two rating categories are used as proxies for hosts' effort: check-in and communication. Still, although guests' feedback may be informative about hosts' effort, reviews are also affected by other factors related to guests' characteristics. To account for such confounding factors, I provide here a hosts' effort estimation using a control function approach. I denote with $\bar{r}^{location}_{i,t}$ the average rating per snapshot for listing i, snapshot t and the category location. Taking advantage of the fact that location should not depend on hosts' effort, in contrast with check-in and communication, I propose the following statistical model:

$$\bar{r}^{location}_{i,t} = \theta_i + guest^{location}_{i,t} \tag{1.7.1}$$

$$\bar{r}^{effort}_{i,t} = e_{i,t} + guest^{effort}_{i,t}, \tag{1.7.2}$$

where θ_i is the fixed quality of listing i; $e_{i,t}$ is the effort exerted by the host of listing i at snapshot t; $guest^{location}_{i,t}$ and $guest^{effort}_{i,t}$ account for the guests' specific characteristics about the location and effort such as attitude, tastes or generosity. The control function approach relies on the following equation:

$$guest^{effort}_{i,t} = \alpha + \beta guest^{location}_{i,t} + \epsilon_{i,t}, \tag{1.7.3}$$

with $E(guest^{location}_{i,t}\epsilon_{i,t}) = 0$ and $\beta \neq 0$. Equation 1.7.3 assumes a common linear relationship between guests' characteristics for all ratings in the dataset. It allows guests to have different values of $guest^{location}_{i,t}$ and $guest^{effort}_{i,t}$, but a common linear relationship is always present for every guest up to the orthogonal error $\epsilon_{i,t}$.[25] Plugging Equation 1.7.3 into the previous system of equations, I derive the following fixed effect panel regression:

$$\begin{aligned}
\bar{r}^{effort}_{i,t} &= e_{i,t} + guest^{effort}_{i,t} \\
&= e_{i,t} + \alpha + \beta guest^{location}_{i,t} + \epsilon_{i,t} \\
&= e_{i,t} + \alpha + \beta(\bar{r}^{location}_{i,t} - \theta_i) + \epsilon_{i,t} \\
\bar{r}^{effort}_{i,t} &= \alpha - \beta\theta_i + \beta\bar{r}^{location}_{i,t} + e_{i,t} + \epsilon_{i,t}. \qquad (1.7.4)
\end{aligned}$$

In Equation 1.7.4, $\bar{r}^{effort}_{i,t}$ is regressed on $\bar{r}^{location}_{i,t}$ with a constant and a listing fixed effect accounting for $\alpha - \beta\theta_i$. Accordingly, the host effort $e_{i,t}$ can be estimated from the residuals of fixed effect panel regression with noise $\epsilon_{i,t}$. To have a consistent estimate of β (and unbiased measures of effort), the following orthogonality conditions need to hold:

$$E[\bar{r}^{location}_{i,t}\epsilon_{i,t}|\theta_i] = 0 \tag{OC_1}$$

$$E[\bar{r}^{location}_{i,t}e_{i,t}|\theta_i] = 0. \tag{OC_2}$$

Condition OC_1 directly follows from the assumption 1.7.3 and the orthogonality of the error $\epsilon_{i,t}$ with $guest^{location}_{i,t}$. Differently, condition OC_2 imposes hosts' effort to not be correlated with deviations of $\bar{r}^{location}_{i,t}$ from the fixed quality θ_i.

I provide empirical evidence supporting condition OC_2 studying the relationship between the effort measures $e^{check}_{i,t}$, $e^{comm}_{i,t}$, the location rating $\bar{r}^{location}_{i,t}$ and a different proxy for hosts' effort present in the dataset: hosts' response rate. This variable represents the percentage of new inquiries or lodging requests to which the host responded within 24 hours in the past 30 days before each snapshot.[26] In case of hosts with multiple listings, the variable does not adjust and it considers all new inquires received by a host. To account for this, I restrict the analysis to single listings, i.e. listings whose hosts do not manage multiple properties on Airbnb.[27] I regress the variable hosts' response rate over the effort measures $e^{check}_{i,t}$, $e^{comm}_{i,t}$, and the location rating $\bar{r}^{location}_{i,t}$ controlling for listing fixed effects (see Table 1.12).[28] The results support condition

[25] The common relationship can be relaxed allowing the parameter β to change over time-invariant group of listings. Still, all results presented in this Section do not qualitatively change when I allow for different values of β with a random coefficient approach (see Appendix 1.13.2).

[26] For more information regarding how the response time is computed, see the official Airbnb webpage at www.airbnb.com/help/article/430/what-is-response-rate-and-how-is-it-calculated.

[27] At each snapshot I observe listing and host identification numbers. Single listings constitute the 48 percent of total amount of Airbnb listings in the dataset.

[28] The variable hosts' response rate takes values from 0 to 1. A higher percentage corresponds to a faster rate of host's replies.

OC_2: hosts' response rate is not significantly correlated with deviations of $\bar{r}^{location}_{i,t}$, whereas it is positively and significantly correlated with the effort dimensions.

In the remaining part of the Section, I study hosts' effort showing the previous results using the effort measures $e^{check}_{i,t}$, $e^{comm}_{i,t}$ estimated as residuals of the regression in Equation 1.7.4. The identification strategy presented in Section 1.4 can be replicated using $e^{check}_{i,t}$, $e^{comm}_{i,t}$ as proxies for hosts' effort.[29] Table A.12 presents the OLS panel regressions of hosts' effort and the number of competitors as shown in Equation 1.4.1. These regressions show not significant results, similar to the case of ratings $\bar{r}^{effort}_{i,t}$ (Table 1.4). Demand-driven confounding factors are likely at place and endogeneity issues affect the regressions' coefficients. Thus, I estimate the effect of competition over hosts' effort considering variations in the number of competitors due to the Settlement Agreement. First, I present results about the "reduced form" of the IV estimates considering the functional form of Equation 1.5.1. Table 1.13 shows the results. The negative relationship between the instrument $\gamma^j_i \times post_{Nov2017}$ and hosts' effort holds, and it is statistically significant for both measures $e^{check}_{i,t}$ and $e^{comm}_{i,t}$. The economic significance of the relationship is also present. When $\gamma^{0.5}_i$ changes from 0 to 1, $e^{check}_{i,t}$ and $e^{comm}_{i,t}$ decrease by almost 0.2 units; and longer distances, γ^1_i and γ^2_i, are associated with drops greater than 0.2 units. It is important to recall that, because of its nature of residuals, the measure has a zero sample mean with standard deviation equal to 0.47. Thus, a change of 0.2 accounts for almost one half of standard deviation. Similar results characterize the IV estimates, presented in Table 1.14. A negative relationship between the number of competitors and hosts' effort is present for $e^{check}_{i,t}$ and $e^{comm}_{i,t}$. Accordingly, the negative relationship between number of competitors and hosts' effort holds even after removing confounding factors due to guests' characteristics.

Table 1.12: Evidence Supporting Assumption OC_2: Response Rate, $\bar{r}^{location}_{i,t}$, $e_{i,t}$

	Response rate	Response rate	Response rate
$\bar{r}^{location}_{i,t} \times 100$	0.0661		
	[0.0499]		
$e^{comm}_{i,t} \times 100$		0.216**	
		[0.106]	
$e^{check}_{i,t} \times 100$			0.314***
			[0.112]
Listing FE	✓	✓	✓
Mean	0.973	0.974	0.974
R-squared	0.000052	0.0002354	0.0005736
N	50,432	49,650	49,615

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. Standard errors clustered by listing are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[29] I use information regarding all listings in the dataset to compute the effort measures by Equation 1.7.4. To replicate the previous analysis I consider the same restrictions as in Section 1.5. The number of observations are slightly different relative to the previous analysis since I have to exclude listings with missing information about $\bar{r}^{location}_{i,t}$ to estimate the effort measures.

Table 1.13: Impact of the Settlement Agreement on the Estimated Hosts' Effort (Reduced Form)

	$e_{i,t}^{check-in}$			$e_{i,t}^{comm}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\gamma_i^{0.5} \times post_{Nov2017}$	-0.161**			-0.117*		
	[0.0640]			[0.0604]		
$\gamma_i^{1} \times post_{Nov2017}$	-0.238**			-0.201**		
		[0.0948]			[0.0856]	
$\gamma_i^{2} \times post_{Nov2017}$			-0.277**			-0.191*
			[0.114]			[0.101]
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	0.00629	0.00630	0.00629	0.00724	0.00724	0.00724
R^2	0.0034	0.0034	0.0034	0.0033	0.0034	0.0033
N	55,633	55,640	55,654	55,633	55,640	55,654

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. Standard errors clustered by listing are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.14: IV Estimates of the Impact of Competition on the Estimated Hosts' Effort

	$e_{i,t}^{check-in}$			$e_{i,t}^{comm}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(L_{i,t}^{0.5})$	-0.107**			-0.0778*		
	[0.0430]			[0.0405]		
$\ln(L_{i,t}^{1})$		-0.0959**			-0.0810**	
		[0.0383]			[0.0346]	
$\ln(L_{i,t}^{2})$			-0.0861**			-0.0594*
			[0.0353]			[0.0314]
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	0.0063	0.0063	0.0063	0.0072	0.0072	0.0072
R^2	0.0000888	0.000144	0.000288	0.000117	0.000160	0.000442
N	55,633	55,640	55,654	55,633	55,640	55,654

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. Standard errors clustered by listing are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

1.7.2 Controlling for the Composition of Competitors

Until now, I used the total number of short-term listings around to describe the intensity of competition faced by each listing. Yet, the profile of competitors around each listing may be also relevant to determine the competitiveness of the area in which the listing is located. This point may be a concern for what regards the identification strategy since the enforcement of the regulation modified the profile of listings active on the platform.

To partially account for potential changes in the composition of competition, I present in Appendix the same results of Section 1.5 controlling for the following set of variables: $z_{i,t}^{j,shared}$, the ratio between short-term listings renting shared apartments and short-term listings renting entire apartments within j kilometers of listing i; $z_{i,t}^{j,super}$, the ratio between superhost short-term listings and non-superhost short-term listings within j kilometers of listing i; $z_{i,t}^{j,90/100}$, the ratio between short-term listings with rating $\bar{R}_{i,t}$ lower than 4 and short-term listings with rating $\bar{R}_{i,t}$ equal to 5 within j kilometers of listing i; $z_{i,t}^{j,90-100/100}$, the ratio between short-term listings with rating $\bar{R}_{i,t}$ between 4 and 5 and short-term listings with rating $\bar{R}_{i,t}$ equal to 5 within j kilometers of listing i; $z_{i,t}^{j,acc1/5}$, the ratio between short-term listings that can accommodate only one guest and short-term listings that can accommodate more than five guests within j kilometers of listing i; $z_{i,t}^{j,acc2/5}$, the ratio between short-term listings that can accommodate only two guests and short-term listings that can accommodate more than five guests within j kilometers of listing i; $z_{i,t}^{j,acc3-4/5}$, the ratio between short-term listings that can accommodate three, four or five guests and short-term listings that can accommodate more than five guests within j kilometers of listing i.

Tables A.16, A.17, A.18, A.19 shows the results. The OLS estimates Table A.16 are statistically insignificant; whereas the "first stage" coefficients (Table A.17) continue to be strongly positive significant. The reduced form and the IV estimates in Tables A.18 and A.19 are negative and significant except for the 2km-radius specification. Interestingly, the magnitude of the IV estimates is similar relative to the coefficients in Section 1.5. This suggests that variations in the profile of competitors do not alter the negative relationship between effort and the number of competitors that motivates this analysis.

1.8 Conclusion

In this work I provide theoretical and empirical evidence regarding the negative effect on the incentives to exert effort of the number of competitors using a model of reputation concerns. First, I develop a reputation model in a directed search framework where movements in entry costs impact the number of hosts in the market and their incentives to exert effort. Then, using a unique dataset of Airbnb, I identify the causal relationship between the number of competitors on the platform and hosts' effort. To do so, I consider a change in the regulation regarding the registration enforcement of Airbnb hosts in San Francisco in September 2017. I obtain a negative and significant effect regarding the extent of competition over hosts' effort. All empirical results are in line with the main predictions of the model.

The main limitation of my work regards the structure of the dataset and the available pieces of information concerning transactions and effort. All the proxies that I use to estimate hosts' effort are extracted from the Airbnb feedback system. In this sense, my analysis considers only the hosts' effort exerted in reviewed transactions.

From a policy perspective, the results of my work suggest that limiting the number of competitors in a platform increases the profits of those agents who remain and it may be beneficial in terms of services' quality. In addition to hosts' (positive) selection, hosts have stronger incentives to exert effort and provide good quality services.

Accordingly, rental restrictions, such as the San Francisco Short-Term Rentals Regulation, favor local hosts complying with the regulatory terms without undermining hosts' quality provision. Moreover, this work sheds light on a trade-off between quantity and quality of transactions in the context of platform design. Several platforms (Airbnb included) charge a percent fee on the total price of each transaction between agents. Therefore they have incentives to lower entry costs, attract more users and foster more exchanges. Still, my work shows that an increase in entry costs leads hosts to charge higher prices and exert more effort. Transactions' quality increases as well as platform's profit per transaction. Thus, the total effect of an increase in entry costs on platforms' profit is ambiguous. In line with these policy implications, further research is necessary to investigate the optimal entry fee for the efficiency of the market and for platforms.

Appendix A

1.9 Appendix: Model

Here I provide proofs of the Propositions and Theorems discussed in Section 1.2. Before doing that, I briefly discuss the hosts optimal pricing if the cost of effort becomes public information after being drawn by hosts. I show that this allocation may not be sustained when the cost of effort is hosts' private information. Then, in the context of asymmetry of information, I characterize non-reputational equilibria with separating strategies in prices pointing out the additional conditions that are necessary for their existence. Finally, I characterize the constrained efficient reputational equilibrium allocation and I proceed with the proofs.

1.9.1 Perfect Information

With public information about hosts' cost of effort, the effort exerted in period 1 and the price posted in period 2 do not impact guests' beliefs. In period 2, the problem for hosts who draw $c = 0$ is defined as follows:

$$\begin{aligned} &\max_{p_2} \; p_2\alpha(\theta_2) \\ &s.t. \;\; (a+b-p_2)\frac{\alpha(\theta_2)}{\theta_2} = U_2, \end{aligned}$$

where U_2 is the guests' expected utility for a match with hosts in period 2. Accordingly, the optimal price and tightness for hosts with $c = 0$, p_2^0, θ_2^0 are defined in terms of U_2. If $a+b < U_2$, then $\theta_2^0 = 0$ and $p_2^0 = 0$. If $a+b \geq U_2$:

$$\begin{aligned} \alpha'(\theta_2^0) &= \frac{U_2}{a+b} \\ p_2^0 &= a+b-\frac{\theta_2^0}{\alpha(\theta_2^0)}U_2. \end{aligned} \tag{1.9.1}$$

Thus, the expected profit with public information for hosts with $c = 0$ is defined as follows:

$$\Pi_2(a+b) = (a+b)(\alpha(\theta_2^0) - \alpha'(\theta_2^0)\theta_2^0), \tag{1.9.2}$$

where θ_2^0 is defined by Equation 1.9.1. The expected profit is increasing in the guests' surplus of transactions $(a+b)$ if $a+b \geq U_2$:

$$\begin{aligned} \frac{\partial \Pi_2(a+b)}{\partial(a+b)} &= \alpha(\theta_2^0) - \alpha'(\theta_2^0)\theta_2^0 + (a+b)\frac{\partial(\alpha(\theta_2^0) - \alpha'(\theta_2^0)\theta_2^0)}{\partial\theta_2^0}\frac{\partial\theta_2^0}{\partial(a+b)} \\ &= \alpha(\theta_2^0) - \alpha'(\theta_2^0)\theta_2^0 - (a+b)\alpha''(\theta_2^0)\theta_2^0\frac{\partial\theta_2^0}{\partial(a+b)} \\ &= \alpha(\theta_2^0) - \alpha'(\theta_2^0)\theta_2^0 + (a+b)\alpha''(\theta_2^0)\theta_2^0\frac{1}{\alpha''(\theta_2^0)}\frac{U_2}{(a+b)^2} \\ &= \alpha(\theta_2^0) > 0, \end{aligned}$$

where the third passage directly follows from the properties of the derivative of the inverse function.[30] Conversely, the expected profit is decreasing in U_2 if $a + b \geq U_2$:

$$\begin{aligned}
\frac{\partial \Pi_2(a+b)}{\partial U_2} &= (a+b)\frac{\partial(\alpha(\theta_2^0) - \alpha'(\theta_2^0)\theta_2^0)}{\partial \theta_2^0}\frac{\partial \theta_2^0}{\partial U_2} \\
&= -(a+b)\alpha''(\theta_2^0)\theta_2^0\frac{\partial \theta_2^0}{\partial U_2} \\
&= -(a+b)\alpha''(\theta_2^0)\theta_2^0\frac{1}{\alpha''(\theta_2^0)}\frac{1}{(a+b)} \\
&= -\theta_2^0 < 0.
\end{aligned}$$

Similarly, in period 2, the problem for hosts who draw $c = k > 0$ is defined as follows:

$$\begin{aligned}
&\max_{p_2} \; p_2\alpha(\theta_2) \\
&s.t. \;\; (b - p_2)\frac{\alpha(\theta_2)}{\theta_2} = U_2.
\end{aligned} \tag{1.9.3}$$

If $b < U_2$, then the optimal price and tightness for hosts with cost of effort $c = k > 0$ p_2^k, θ_2^k are $p_2^k = 0$ and $\theta_2^k = 0$. If $b \geq U_2$:

$$\begin{aligned}
\alpha'(\theta_2^k) &= \frac{U_2}{b} \\
p_2^k &= b - \frac{\theta_2^k}{\alpha(\theta_2^k)}U_2.
\end{aligned} \tag{1.9.4}$$

Thus, the expected profit with public information for hosts with $c = k > 0$ is defined as follows:

$$\Pi_2(b) = (b)(\alpha(\theta_2^k) - \alpha'(\theta_2^k)\theta_2^k), \tag{1.9.5}$$

where θ_2^k is defined by Equation 1.9.4. Similarly to the case of hosts with cost of effort $c = 0$, the expected profit is increasing in b and decreasing in U_2 if $b \geq U_2$:

$$\begin{aligned}
\frac{\partial \Pi_2(b)}{\partial b} &= \alpha(\theta_2^k) > 0 \\
\frac{\partial \Pi_2(b)}{\partial U_2} &= -\theta_2^k < 0.
\end{aligned}$$

Hosts who did not match with guests in period 1 do not draw their cost of effort and, together with new arrivals solve the following problem in period 2.

$$\begin{aligned}
&\max_{p_2} \; p_2\alpha(\theta_2) \\
&s.t. \;\; (a\pi + b - p_2)\frac{\alpha(\theta_2)}{\theta_2} = U_2.
\end{aligned} \tag{1.9.6}$$

[30] Recall that the first derivative of the function α is invertible by Assumption 1.

The ex-ante guests' utility from a transaction with this class of hosts is $a\pi + b$ since, with probability π hosts draw zero cost of effort and then they exert effort $e_2 = 1$. Otherwise, with probability $1-\pi$ they draw positive cost of effort and they have no incentives to exert effort: $e_2 = 0$. Accordingly, if $a\pi + b < U_2$, the optimal price and tightness for these hosts, $p_2^{\emptyset}$, $\theta_2^{\emptyset}$ are $p_2^{\emptyset} = 0$ and $\theta_2^{\emptyset} = 0$. If $a\pi + b \geq U_2$:

$$\begin{aligned} \alpha'(\theta_2^{\emptyset}) &= \frac{U_2}{a\pi + b} \\ p_2^{\emptyset} &= a\pi + b - \frac{\theta_2^{\emptyset}}{\alpha(\theta_2^{\emptyset})} U_2. \end{aligned} \tag{1.9.7}$$

Thus, the expected profit for hosts who did not match with guests in period 1 and for new arrivals is defined as follows:

$$\Pi_2(a\pi + b) = (a\pi + b)(\alpha(\theta_2^{\emptyset}) - \alpha'(\theta_2^{\emptyset})\theta_2^{\emptyset}), \tag{1.9.8}$$

where $\theta_2^{\emptyset}$ is defined by Equation 1.9.7.

In period 1, hosts have not yet drawn their cost of effort and their problem is the following:

$$\begin{aligned} &\max_{p_1} \ (p_1)\alpha(\theta_1) + \beta\alpha(\theta_1)(\pi\Pi_2(a+b) + (1-\pi)\Pi_2(b)) + \beta(1-\alpha(\theta_1))\Pi_2(a\pi + b) \\ &s.t. \ (a\pi + b - p_1)\frac{\alpha(\theta_1)}{\theta_1} = U_1. \end{aligned} \tag{1.9.9}$$

The ex-ante guests' utility from a transaction in period 1 is a$\pi + b$ since hosts who draw positive cost of effort have no incentives to exert effort: their cost of effort is public information and they cannot commit to exert effort in period 2. Thus, if $a\pi + b + \beta(\pi\Pi_2(a+b) + (1-\pi)\Pi_2(b) - \Pi_2(a\pi + b)) < U_1$, the optimal price and tightness for these hosts, $p_1^{\emptyset}$, $\theta_1^{\emptyset}$ are $p_1^{\emptyset} = 0$ and $\theta_1^{\emptyset} = 0$. Otherwise:

$$\begin{aligned} \alpha'(\theta_1^{\emptyset}) &= \frac{U_1}{a\pi + b + \beta(\pi\Pi_2(a+b) + (1-\pi)\Pi_2(b) - \Pi_2(a\pi + b))} \\ p_1^{\emptyset} &= a\pi + b - \frac{\theta_1^{\emptyset}}{\alpha(\theta_1^{\emptyset})} U_1. \end{aligned} \tag{1.9.10}$$

If the cost of effort is hosts' private information, the equilibrium above may not be sustained. Hosts are better-off posting p_2^0 relative to p_2^k. This follows since U_2 is the same for hosts with different cost of effort. Thus, $\alpha'(\theta_2^0) < \alpha'(\theta_2^k)$ from Equations 1.9.1 and 1.9.4. Then, by the concavity of α, $\theta_2^0 > \theta_2^k$ and $\alpha(\theta_2^0) > \alpha(\theta_2^k)$: hosts with $c = 0$ have higher chances to be matched with guests relative to hosts with $c = k$. Hence, hosts are better-off posting p_2^0 with expected profits equal to $p_2^0\alpha(\theta_2^0)$:

$$\begin{aligned} p_2^0\alpha(\theta_2^0) &= (a+b)(\alpha(\theta_2^0) - \alpha'(\theta_2^0)\theta_2^0) \\ &> b(\alpha(\theta_2^0) - \alpha'(\theta_2^0)\theta_2^0) > b(\alpha(\theta_2^k) - \alpha'(\theta_2^k)\theta_2^k) \end{aligned}$$

where the inequality in the last passage in due to Assumption 1: $\alpha(\theta) - \alpha'(\theta)\theta > 0 \ \forall\theta$ and $\frac{\partial(\alpha(\theta) - \alpha'(\theta)\theta)}{\partial\theta} = -\alpha''(\theta)\theta > 0$.

Accordingly, the perfect information equilibrium may not be sustained if the cost of effort is hosts' private information. In particular, if the following condition holds, hosts who draw cost $c = k > 0$ are willing to exert effort, incur in cost k and obtain future expected profits $p_2^0\alpha(\theta_2^0)$:

$$\beta(p_2^0\alpha(\theta_2^0) - p_2^k\alpha(\theta_2^k)) \geq c. \tag{1.9.11}$$

If the condition in 1.9.11 does not hold, then the perfect information equilibrium allocation can be sustained. In the next Section, I will show how this allocation is a particular case of reputational equilibrium.

1.9.2 Non-Reputational Equilibria

In this paper I focus on reputational equilibria where the information provided by hosts' histories is not made ineffective by the prices posted in period 2. Here I briefly discuss non-reputational equilibria.

As mentioned in the main text, in non-reputational equilibria, hosts with different cost of effort play separate pricing strategies in period 2. Accordingly, guests can perfectly infer hosts' cost of effort observing period 2 prices irrespectively of hosts' histories. In equilibrium, hosts who draw cost $c = k > 0$ post in period 2 the perfect information price p_2^k. Differently, hosts who draw cost $c = 0$ post in period 2 price $p_2^{sep} > 0$ such that hosts with cost $c = k > 0$ are better-off posting p_2^k. In this sense, the existence of non-reputational equilibria relies on the fact that the profit $p_2^k\alpha(\theta_2^k)$ is strictly positive, that is $b > U_2$. If this condition holds, then the following two incentive compatibility constraints have to be satisfied:

$$p_2^k\alpha(\theta_2^k) \geq p_2^{sep}\alpha(\theta_2^{sep})$$
$$p_2^{sep}\alpha(\theta_2^{sep}) \geq p_2^k\alpha(\theta_2^k).$$

The ex-ante utility for guests who are matched with hosts posting p_2^k is b; whereas, the utility for those matched with hosts posting p_2^{sep} is $a + b$:

$$(b - p_2^k)\frac{\alpha(\theta_2^k)}{\theta_2^k} = U_2 = (a + b - p_2^{sep})\frac{\alpha(\theta_2^{sep})}{\theta_2^{sep}}. \tag{1.9.12}$$

From the incentive compatibility constraints it results that, when host with $c = 0$ separate, they do not increase their expected profits since $p_2^k\alpha(\theta_2^k) = p_2^{sep}\alpha(\theta_2^{sep})$. In particular, from Equation 1.9.12, $p_2^{sep} > p_2^k$ and $\theta_2^{sep} > \theta_2^k$. Accordingly, the existence of this equilibrium relies on hosts' willingness to separate even when their expected profits do not increase after separating.

1.9.3 Reputational Equilibria

I focus on reputational equilibria for two reasons. First, empirical evidence suggests that prices do not fully reveal users' private type. Histories (reviews) are important to reduce the asymmetry of information in digital platforms.[31] Moreover, outside the class of reputational

[31] Cabral and Hortaçsu (2010), Fan et al. (2016), and Jolivet et al. (2016) show evidence regarding the significant impact of reviews on sellers' profitability in several online marketplaces.

equilibria, hosts who draw a positive cost of effort in period 1 do not exert effort in any of the two periods ($e_1(k) = e_2(k) = 0$). Differently, in reputational equilibria, hosts who draw a positive cost may exert effort in period 1 ($e_1(k) = 1$) in order to mimic hosts with $c = 0$ and get a price premium in period 2. Thus, since exerting effort is efficient ($a > c$), reputational equilibria are Pareto superior in terms of the ex-post surplus of transactions relative to other non-reputational equilibria.

Pooling strategies in prices for hosts with the same history in period 2 characterize the class of reputational equilibria. In period 1, all hosts post the same price since the cost of effort is drawn after matches are formed. Accordingly, guests in both periods cannot infer hosts' costs directly from prices in period 1. After transactions occur, hosts have different histories depending on the reported effort, which affect guests' beliefs $\bar{\mu}_2$ about hosts' effort choice in the future. In period 2, hosts with the same history post the same price. In particular, hosts who were not matched in period 1 and new entrants post the same price since their cost of effort is drawn after matches. The case is similar for hosts who were matched in period 1. By pooling in prices, hosts with $c = k > 0$ obtain a price premium in period 2 if they exert effort in period 1. It constitutes the reputational benefit (the "carrot") of having exerted effort. Conversely, if hosts with $c = k > 0$ do not exert effort, they cannot pool in period 2 and their cost is fully disclosed (the "stick"). Price pooling is vital to implement the "carrot-stick strategy" that characterizes reputational equilibria. Multiple prices can sustain these equilibria and a continuum of equilibria is present in this class. In the main text, I restrict my analysis to the price profile that implements the constrained efficient equilibrium allocation and maximizes hosts' profits. To do so, I consider guests' beliefs that disregard the additional signaling role of prices in period 2: for any posted price, guests in period 2 do not update their beliefs about hosts' cost of effort (formed observing the host's history). This restriction is not necessary since a wide range of guests' beliefs sustains the constrained efficient equilibrium allocation. Disregarding the signaling from prices in period 2 is justified by the following observation. Independently of their cost of effort, hosts with the same history in period 2 have the same profit function: hosts with $c = k > 0$ do not exert effort in period 2 and their expected profits are $p_2\alpha(\theta_2)$; similarly, hosts with $c = 0$ do exert effort (that is costless for them) and get $p_2\alpha(\theta_2)$ as well. Accordingly, the optimal pricing strategy is aligned for both hosts' types and guests may not update their beliefs after observing prices in period 2. Furthermore, thanks to the equality of the profit function in period 2 for hosts with different costs of effort, reputational pooling equilibria are *not* eliminated by refinements such as the intuitive criterion by Cho and Kreps (1987).

Here I provide the proofs of the Propositions and Theorems discussed in Section 1.2. At the same time, I illustrate the constrained efficient allocation and I show that the prices posted by hosts in the equilibrium respect the Hosios (1990) conditions.

The constrained efficient allocation is the allocation that a benevolent social planner would choose taking as given the following elements:

- the frictions that characterize the matching between hosts and guests;
- the hosts' entry cost f;
- the hosts' private information concerning the cost of effort.

Accordingly, the social planner aims at allocating guests to hosts in order to implement the efficient hosts' entry and effort provision.

In line with the main text, I start my analysis from period 2.

Period 2

In order to implement the efficient hosts' entry in period 2, the social planner faces the following problem:

$$\max_{\theta_2}(a\pi + b)\frac{\alpha(\theta_2)}{\theta_2} - \frac{f}{\theta_2}$$

The factor $(a\pi + b)\frac{\alpha(\theta_2)}{\theta_2}$ represents the expected surplus from a transaction for each guest, whereas $\frac{f}{\theta_2}$ defines the hosts' entry costs for each guest. The optimal θ_2^* that maximizes the social planner objective function is such that:

$$(a\pi + b)(\alpha(\theta_2^*) - \alpha'(\theta_2^*)\theta_2^*) = f \tag{1.9.13}$$

It is possible to note that the optimal price posted by hosts who enter the platform in period 2, $p_2^{\emptyset}$ implements the efficient entry condition of period 2 when the hosts' free entry condition is binding. The optimal expected profits for new entrant hosts is defined by Equation 1.9.8 and it equals the LHS of Equation 1.9.13.

Accordingly, the latter condition equalizes the optimal expected profits for new entrant hosts to the entry costs f: i.e. it imposes a binding free entry condition for entrant hosts in period 2. The rule proposed by Hosios (1990) states that hosts' entry is constrained efficient when the two sides of the market share the ex-ante surplus of transactions (in this case $a\pi + b$) according to the elasticity of the matching function with respect to the tightness. In fact, in this case the expected profits for new entrant hosts, $\Pi_2(a\pi + b)$, and the guests' expected utility, U_2, are defined as follows:

$$\Pi_2(a\pi + b) = p_2^{\emptyset}\alpha(\theta_2^{\emptyset}) = (a\pi + b)(1 - \epsilon_2^{\emptyset})\alpha(\theta_2^{\emptyset})$$
$$U_2 = (a\pi + b)\epsilon_2^{\emptyset}\frac{\alpha(\theta_2^{\emptyset})}{\theta_2^{\emptyset}},$$

where $\epsilon_2^{\emptyset} = \alpha'(\theta_2^{\emptyset})\frac{\theta_2^{\emptyset}}{\alpha(\theta_2^{\emptyset})}$ denotes the elasticity of the matching function with respect to the tightness calculated at $\theta_2^{\emptyset}$.

I analyze the constrained efficient allocation for hosts who enter in period 1 in the next Section. In period 2 they post prices to maximize their profits given guests' beliefs $\bar{\mu}_2(h)$ and U_2.

Proof of Proposition 1. Assuming that guests do not update their beliefs about hosts' cost of effort after observing prices in period 2, hosts who were matched in period 1 and with history

h solve the following problem in period 2:

$$\max_{p_2} \; p_2\alpha(\theta_2) \tag{1.9.14}$$
$$s.t. \; (a\bar{\mu}_2(h) + b - p_2)\frac{\alpha(\theta_2)}{\theta_2} = U_2.$$

If $a\bar{\mu}_2(h) + b < U_2$, then the optimal price and tightness $p_2^{pool}(h)$, $\theta_2^{pool}(h)$ are $p_2^{pool}(h) = 0$ and $\theta_2^{pool}(h) = 0$. If $a\bar{\mu}_2(h) + b \geq U_2$:

$$\alpha'(\theta_2^{pool}) = \frac{U_2}{a\bar{\mu}_2(h) + b} \tag{1.9.15}$$
$$p_2^{pool} = a\bar{\mu}_2(h) + b - \frac{\theta_2^{pool}}{\alpha(\theta_2^{pool}}U_2.$$

Similarly, hosts who were not matched in period 1 and new entrants solve the problem in Equation 1.9.6 and their optimal price and tightness $p_2^{\emptyset}(h), \theta_2^{\emptyset}(h)$ are reported in Equation 1.9.7.

□

It is possible to note that the optimal prices for hosts who enter in period 1 follow Hosios (1990) conditions since hosts and guests share the ex-ante surplus $a\bar{\mu}_2(h) + b$ according to the elasticity of the matching function. In particular:

$$\Pi_2(a\bar{\mu}_2(h) + b) = p_2^{pool}(h)\alpha(\theta_2^{pool}(h)) = (a\bar{\mu}_2(h) + b)(1 - \epsilon_2^{pool}(h))\alpha(\theta_2^{pool}(h))$$
$$U_2 = (a\bar{\mu}_2(h) + b)\epsilon_2^{pool}(h)\frac{\alpha(\theta_2^{pool}(h))}{\theta_2^{pool}(h)},$$

where $\epsilon_2^{pool}(h) = \alpha'(\theta_2^{pool}(h))\frac{\theta_2^{pool}(h)}{\alpha(\theta_2^{pool}(h))}$ denotes the elasticity of the matching function with respect to the tightness calculated at θ_2^{pool}.Accordingly, the ex-ante surplus of transactions in period 2 is greater for hosts who exert effort in period 1. Furthermore, hosts who exert effort in period 1 get a greater share of the surplus since the elasticity $\epsilon_2^{pool}(h)$ is decreasing in the tightness and $\theta_2^{pool}(h) > \theta_2^k \; \forall \bar{\mu}_2(h)0$. In this sense, in order to increase the effort provision (in period 1) and obtain the efficient hosts' entry in period 2, the social planner may commit to allocate guests to hosts in period 2 such that the tightness levels $\theta_2^{pool}(h), \theta_2^{\emptyset}$ 2 are formed.

Period 1

In line with the analysis in the main text, I start with the proof of Proposition 2 regarding the effort provision in period 1. Then, I provide the proof for Proposition 3 and I characterize the constrained efficient allocation in period 1.

Proof of Proposition 2. The effort strategy by hosts with $c = k > 0$ in period 1 realizes the interest of these hosts to mimic hosts with $c = 0$, post higher prices and attract more guests as it has been observed in Proposition 1. In particular, exerting $e_1 = 1$, hosts with $c = k > 0$ pool together with hosts with $c = 0$ in period 2, posting $p_2^{pool}(e_1 = 1)$. Exerting $e = 0$, with $c = k > 0$ cannot pool anymore since their history is fully revealing their costs. The value of pooling depends on the guests' interim beliefs. They are derived by the Bayes formula when possible:

$$\bar{\mu}_2(e_1 = 1) = \frac{\pi}{\pi + (1-\pi)\omega} \tag{1.9.16}$$

$$\bar{\mu}_2(\emptyset) = \pi \tag{1.9.17}$$

$$\bar{\mu}_2(e_1 = 0) = 0, \tag{1.9.18}$$

where $\omega \in [0, 1]$ is the probability to exert effort $e_1 = 1$ by hosts with $c = k > 0$ in equilibrium in period 1. In this sense, the discounted marginal benefits of exerting effort for non-commitment types are defined as follows:

$$MB = \beta(p_2^{pool}(e_1 = 1)\alpha(\theta_2^{pool}(e_1 = 1)) - p_2^{pool}(e_1 = 0)\alpha(\theta_2^{pool})(e_1 = 0)).$$

Recalling the function $\Pi_2(.)$ introduced in the previous Section, the discounted marginal benefits can be defined as follows:

$$MB = \beta\Bigg(\Pi_2\Big(a\frac{\pi}{\pi + (1-\pi)\omega} + b\Big) - \Pi_2(b)\Bigg),$$

where the function $\Pi_2(.)$ is weakly increasing in the value of $a\bar{\mu}_2(h) + b$. Hosts with $c = k > 0$ compare MB with the cost of effort k. The following algorithm characterizes the equilibrium level of ω:

1. Consider the case $\omega = 1$ and calculate the MB . If MB is greater than k:

$$\beta\Bigg(\Pi_2\Big(a\frac{\pi}{\pi + (1-\pi)\omega} + b\Big) - \Pi_2(b)\Bigg) \geq k,$$

   then, in equilibrium hosts with $c = k > 0$ exert effort in period 1 with probability $\omega = 1$;

2. If the inequality above does not hold true, then consider the case $\omega = 0$ and calculate again MB. If MB is lower than k:

$$\beta\Bigg(\Pi_2\Big(a\frac{\pi}{\pi + (1-\pi)\omega} + b\Big) - \Pi_2(b)\Bigg) \leq k,$$

   then, in equilibrium hosts with $c = k > 0$ exert effort in period 1 with probability $\omega = 0$;

3. If the two inequalities above do not hold true, then derive $\omega \in (0, 1)$ such that the following equality holds:

$$\beta\Bigg(\Pi_2\Big(a\frac{\pi}{\pi + (1-\pi)\omega} + b\Big) - \Pi_2(b)\Bigg) = k, \tag{1.9.19}$$

   Since the LHS of Equation 1.9.19 is strictly decreasing in ω, it admits only one solution.

$\square$

Proof of Proposition 3. Hosts who enter in period 1 have not yet drawn their cost of effort. Thus, their problem in period 1 is the following:

$$\begin{aligned}
\max_{p_1} \ & (p_1 - k(1-\pi)\omega)\alpha(\theta_1) \\
& + \beta\alpha(\theta_1)\big(\pi\Pi_2\big(a\frac{\pi}{\pi+(1-\pi)\omega}+b\big)+(1-\pi)(1-\omega)\Pi_2(b)\big) \\
& + \beta(1-\alpha(\theta_1))\Pi_2(a\pi+b) \\
s.t. \ & (a(\pi+(1-\pi)\omega)+b-p_1)\frac{\alpha(\theta_1)}{\theta_1} = U_1.
\end{aligned}$$

The ex-ante guests' utility from a transaction in period 1 is $a(\pi+(1-\pi)\omega)+b$ since hosts who draw positive cost of effort exert effort in period 1 with probability ω. Thus, if $a(\pi+(1-\pi)\omega)+b-k(1-\pi)\omega+\beta\Delta\Pi < U_1$, the optimal price and tightness for these hosts, $p_1^{\emptyset}, \theta_1^{\emptyset}$ are $p_1^{\emptyset}=0$ and $\theta_1^{\emptyset}=0$. Otherwise:

$$\begin{aligned}
\alpha'(\theta_1^{\emptyset}) &= \frac{U_1}{a(\pi+(1-\pi)\omega)+b-k(1-\pi)\omega+\beta\Delta\Pi} \\
p_1^{\emptyset} &= a(\pi+(1-\pi)\omega)+b-\frac{\theta_1^{\emptyset}}{\alpha(\theta_1^{\emptyset})}U_1.
\end{aligned}$$

In this sense, if $a(\pi+(1-\pi)\omega)+b-k(1-\pi)\omega+\beta\Delta\Pi \geq U_1$, the expected profits for new entrants in period 1 are defined as follows:

$$\Pi_1 = (a(\pi+(1-\pi)\omega)+b-k(1-\pi)\omega+\beta\Delta\Pi)(\alpha(\theta_1^{\emptyset})-\alpha'(\theta_1^{\emptyset})\theta_1^{\emptyset})+\beta\Pi_2(a\pi+b). \quad (1.9.20)$$

$\square$

The constrained efficient allocation in period 1 implies the efficient hosts' entry and effort provision in period 1. Accordingly, the social planner commits to allocate guests to hosts in period 2 in order to form the tightness levels $\theta_2^{pool}(h), \theta_2^{\emptyset}$. In this sense, hosts who draw cost $c=k>0$ in period 1 have incentives to exert effort with probability ω in line with Proposition 2. Therefore, the social planner solves the following problem in period 1:

$$\max_{\theta_1}(a(\pi+(1-\pi)\omega)+b-k(1-\pi)\omega)\frac{\alpha(\theta_1)}{\theta_1}+\frac{R}{\theta_1}-\frac{f}{\theta_1}$$

Similarly to period 2, the factor $a(\pi+(1-\pi)\omega)+b-k(1-\pi)\omega)\frac{\alpha(\theta_1)}{\theta_1}$ represents the expected surplus from a transaction for each guest, whereas $\frac{f}{\theta_1}$ defines the hosts' entry costs for each guest. Yet, in period 1, an additional element forms the surplus of a transaction. The factor R captures the value of a transaction in updating hosts' reputation and changing the ex-ante surplus of transactions in period 2:

$$R = \beta\alpha(\theta_1)(\pi\Pi_2\big(a\frac{\pi}{\pi+(1-\pi)\omega}+b\big)+(1-\pi)(1-\omega)\Pi_2(b)\big)+\beta(1-\alpha(\theta_1))Pi_2(a\pi+b).$$

The optimal θ_1^* that maximizes the social planner objective function is such that:

$$(a(\pi + (1-\pi)\omega) + b - k(1-\pi)\omega + \beta\Delta\Pi)(\alpha(\theta_1^*) - \alpha'(\theta_1^*)\theta_1^*) + \beta\Pi_2(a\pi + b) = f. \quad (1.9.21)$$

It is possible to note that the optimal price posted by hosts who enter the platform in period 1, $p_1^{\emptyset}$ implements the efficient entry condition of period 1 when the hosts' free entry condition is binding. The optimal expected profits for new entrant hosts is defined by Equation A.20 and it equals the LHS of Equation 1.9.20. Accordingly, the latter condition equalizes the optimal expected profits for new entrant hosts to the entry costs f: i.e. it imposes a binding free entry condition for entrant hosts in period 1.

Existence and Uniqueness

The proof of Theorem 1 has the following structure: first, I assume that a positive measure of hosts enter in period 2. With this assumption, I show the existence and the uniqueness of the equilibrium and I derive the threshold level $\bar{G}$ such that there is entry in the second period for $G > \bar{G}$.

Proof of Theorem 1. With a positive measure of hosts entering in period 2, the free entry condition for hosts in period 2 holds with equality. From the free entry condition and the pricing problem for new entrants (Proposition 1), it is possible to uniquely determine $p_2^{\emptyset}, \theta_2^{\emptyset}$ and U_2. Accordingly, the free entry condition can be written in terms of $\theta_2^{\emptyset}$:

$$(a\pi + b)(\alpha(\theta_2^{\emptyset}) - \theta_2^{\emptyset}\alpha'(\theta_2^{\emptyset})) = f. \quad (1.9.22)$$

From Equation 1.9.22, the equilibrium value of $\theta_2^{\emptyset}$ can be uniquely derived. Recall that $a\pi + b > 0$, $\alpha''(\theta) < 0$, and $\alpha(\theta) - \theta\alpha'(\theta) > 0$ $\forall\theta$. Moreover, $\alpha(\theta) - \theta\alpha'(\theta)$ is strictly increasing in θ. Then, the LHS of Equation 1.9.22 is strictly increasing in θ. For $\theta = 0$, LHS is zero, and the equilibrium value of $\theta_2^{\emptyset}$ is unique and strictly positive with $f > 0$. Using $\theta_2^{\emptyset}$, the equilibrium values of $p_2^{\emptyset}$ and U_2 can be uniquely derived from Equation 1.9.7. With U_2, the values of $p_2^{pool}(h^0)$ and $\theta_2^{pool}(h^0)$ can be uniquely derived by Equation 1.9.4:

$$\alpha'(\theta_2^{pool}(h^0)) = \alpha'(\theta_2^k) = \frac{U_2}{b}$$
$$p_2^{pool}(h^0) = p_2^k = b - \frac{\theta_2^k}{\alpha(\theta_2^k)}U_2,$$

if $b \geq U_2$. Otherwise $\theta_2^{pool}(h^0) = 0$ and $p_2^{pool}(h^0) = 0$. Similarly, the values of $p_2^{pool}(h^1)$ and $\theta_2^{pool}(h^1)$ can be uniquely derived in terms of ω:

$$\alpha'(\theta_2^{pool}(h^1)) = \frac{U_2}{a\frac{\pi}{\pi+(1-\pi)\omega} + b}.$$
$$p_2^{pool}(h^1) = a\frac{\pi}{\pi + (1-\pi)\omega} + b - \frac{\theta_2^{pool}(h^1)}{\alpha(\theta_2^{pool}(h^1))}U_2.$$

As showed early, $\theta_2^{pool}(h^{\emptyset}) > 0$, and $a\pi + b - c > U_2$. Still, since $\frac{\pi}{\pi+(1-\pi)\omega} \geq \pi$, then we have that $a\frac{\pi}{\pi+(1-\pi)\omega} + b > U_2$ and $\theta_2^{pool}(h^1) > 0$. By Proposition 2, ω can be uniquely determined. It follows that also $\theta_2^{pool}(h^1)$ and $p_2^{pool}(h^1)$ are uniquely determined. Accordingly, the equilibrium system of equations uniquely determines all terms regarding period 2.

The expected profits for entrant hosts in period 1 can be rewritten as follows:

$$(p_1^{\emptyset} - k(1-\pi)\omega)\alpha(\theta_1^{\emptyset}) + \beta\alpha(\theta_1^{\emptyset})\Delta\Pi + \beta\Pi_2(a\pi + b),$$

where $\Delta\Pi$ is defined in Proposition 3 and denotes the value of a transaction in terms of reputation updating. Then, by Proposition 3, with $\theta_1^{\emptyset} > 0$:

$$(p_1^{\emptyset} - k(1-\pi)\omega)\alpha(\theta_1^{\emptyset}) + \beta\alpha(\theta_1^{\emptyset})\Delta\Pi = [a(\pi(1-\pi)\omega) + b + \beta\Delta\Pi - k\omega(1-\pi)](1-\epsilon_1^{\emptyset}),$$

where $\epsilon_1^{\emptyset} = \alpha'(\theta_1^{\emptyset})\frac{\theta_1^{\emptyset}}{\alpha(\theta_1^{\emptyset})}$ denotes the elasticity of the matching function with respect to the tightness calculated at $\theta_1^{\emptyset}$. Thus, the free entry condition in period 1 has the following structure:

$$[a(\pi(1-\pi)\omega) + b + \beta\Delta\Pi - k\omega(1-\pi)](1-\epsilon_1^{\emptyset}) + \beta\Pi_2(a\pi + b) = f. \tag{1.9.23}$$

Then, the optimal value of $\epsilon_1^{\emptyset}$ and $\theta_1^{\emptyset}$ can be uniquely derived by Equation 1.9.23. It is possible to note that: $a(\pi(1-\pi)\omega) + b + \beta\Delta\Pi - k\omega(1-\pi) \geq 0$ for all values of θ_1; the value of ϵ_1 is strictly decreasing in θ_1 and $\Pi_2(a\pi + b) \leq f$ by the free-entry condition in period 2. Accordingly, Equation 1.9.23 uniquely characterizes $\theta_1^{\emptyset}$ with $\theta_1^{\emptyset} > 0$. Knowing $\theta_1^{\emptyset}$, I obtain $p_1^{\emptyset}$ and U_1 by Proposition 3, and the measure of entrants in period 1, n_1, by $\theta_1^{\emptyset} = \frac{1}{n_1}$. With n_1, ω, and θ_1^{pool} the measures of hosts who entered in period 1 and have with histories h^1, h^0, and $h^{\emptyset}$ in period 2 are derived as follows:

$$\begin{aligned}
n_2(h^1) &= (\omega n_1(1-\pi) + \pi n_1)\alpha(\theta_1^{\emptyset}) \\
n_2(h^0) &= (1-\omega)n_1(1-\pi)\alpha(\theta_1^{\emptyset}) \\
n_2(h^{\emptyset}) &= n_1(1-\alpha(\theta_1^{\emptyset})).
\end{aligned}$$

Then, with $\theta_2^{pool}(h^1), \theta_2^{pool}(h^0)$, and $\theta_2^{\emptyset}$, the measures of guests who direct their search to hosts with histories h^1, h^0, and $h^{\emptyset}$ posting $p_2^{pool}(h^1), p_2^{pool}(h^0)$ and $p_2^{\emptyset}$, are respectively the following:

$$\begin{aligned}
g_2(h^1) &= \theta_2^{pool}(h^1)n_2(h^1) \\
g_2(h^0) &= \theta_2^{pool}(h^0)n_2(h^0) \\
g_2(h^{\emptyset}) &= G - g_2(h^1) - g_2(h^0).
\end{aligned}$$

Finally, the number of new entrants in period 2 is the difference between the total measure of hosts with history $h^{\emptyset}$ and $n_2(h^{\emptyset})$:

$$\frac{g_2(h^{\emptyset})}{\theta_2^{\emptyset}} - n_2(h^{\emptyset}). \tag{1.9.24}$$

I started the proof assuming that a positive measure of hosts enter in period 2. Still, for some G, the value in Equation 1.9.24 can be negative. In this sense, the proof of the existence and the uniqueness of the equilibrium relies on a value of $G \geq \bar{G}$, with $\bar{G}$:

$$\bar{G} = g_2(h^1) + g_2(h^0) + n_2(h^{\emptyset})\theta_2^{\emptyset}. \tag{1.9.25}$$

$\square$

Testable Predictions

Proof of Proposition 4. The measure of guests present in the market in period 2 is assumed to be big enough to allow hosts' entry in period 2 for both equilibria. Accordingly, the free entry condition is binding for f and f'. Then, $\theta_2'^{\emptyset} > \theta_2^{\emptyset}$ recalling that the expected profits for new entrants is strictly increasing in θ. Moreover, directly from the relationship established in the Proposition 1 between the tightness $\theta_2^{\emptyset}$ and the level of U_2, it results that $U_2 > U_2'$. Accordingly, $\theta_2'^{pool}(h^1) > \theta_2^{pool}(h^1)$ and $\theta_2'^{pool}(h^0) > \theta_2^{pool}(h^0)$ from the Equations in Proposition 1. Accordingly, higher entry costs reduce the number of hosts who enter the market in period 2; thus, the tightness for all hosts increases and the guests' expected utility from the matches decreases. The derivative of the profits over U_2 has already been discussed in Section 1.9.1 using the definition of the function $\Pi_2(.)$. In particular:

$$\begin{aligned}\frac{\partial \Pi_2(a\bar{\mu}_2(h)+b)}{\partial U_2} &= \frac{\partial \Pi_2(a\bar{\mu}_2(h)+b)}{\partial \theta_2^{pool}(h)} \frac{\partial \theta_2^{pool}(h)}{\partial U_2} \\ &= -\theta_2^{pool}(h)\alpha''(\theta_2^{pool}(h)) \left[\alpha'^{-1}\left(\frac{U_2}{a\bar{\mu}_2(h)+b}\right)\right]' = -\theta_2^{pool}(h),\end{aligned}$$

if $U_2 \leq a\bar{\mu}_2 + b$. The last passage directly follows from the properties of the derivative of the inverse function. If $U_2 > a\bar{\mu}_2 + b$, the derivative is equal to zero. Similarly, for those hosts who do not have a transaction in period 1:

$$\frac{\partial \Pi_2(a\pi)+b)}{\partial U_2} = -\theta_2^{\emptyset},$$

if $U_2 \leq a\pi + b$. Otherwise, the derivative is equal to zero. Accordingly, a decrease in U_2 has a greater, positive impact on the expected profits for those hosts with a higher value of θ_2. Taking advantage of this result, it is possible to show that $\omega' \geq \omega$ with the same algorithm used in the proof of Proposition 2:

1. Consider the case in which hosts with $c = k > 0$ exert effort with probability $\omega = 1$ when entry costs are f. Then, in equilibrium:

   $$\beta(\Pi_2(a\pi + b) - \Pi_2(b)) \geq k. \tag{1.9.26}$$

   From the previous results about the derivative of profits in period 2, the LHS of Equation 1.9.26 is greater with f'. Then, hosts with $c = k > 0$ exert effort with probability 1 also with entry costs f': $\omega' = 1$;

2. Consider the case $\omega = 0$ when entry costs are f. Then, in equilibrium:

   $$\beta(\Pi_2(a + b) - \Pi_2(b) \leq k. \tag{1.9.27}$$

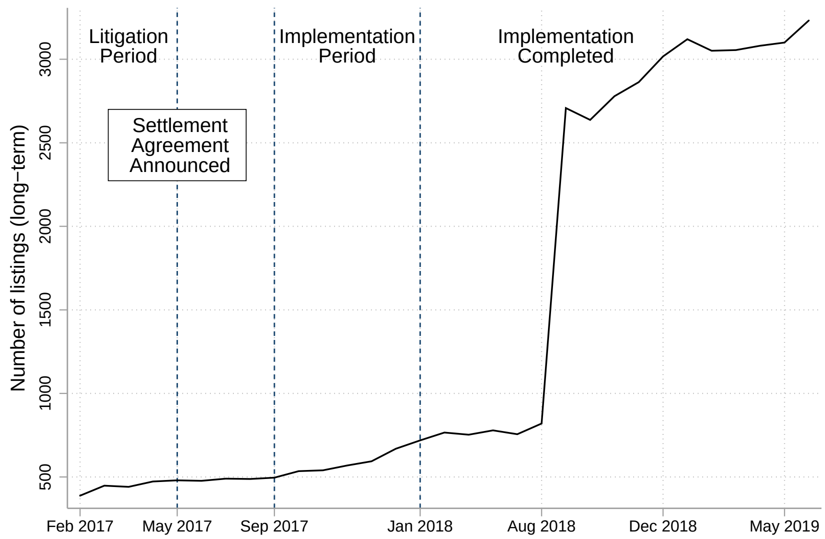
   As before, the LHS of Equation 1.9.27 is greater with f'. Then, Equation 1.9.27 may not be satisfied with f' and, in equilibrium $\omega' \geq 0$;

3. Finally, consider the case in which $\omega \in (0, 1)$ when entry costs are f, such that Equation 1.9.19 is satisfied. With f' the LHS of Equation 1.9.19 increases if $\omega' = \omega$. To restore the equality, the value of ω' has to increase (if possible) so as to decrease the reputation of hosts with history h^1. Thus $\omega' \geq \omega$.

$\square$

1.10 Appendix: Empirical Setting and Dataset

Figure A.1: Long-Term Airbnb Listings over Time



Note: The figure plots the total number of Airbnb listings that do *not* offer short-term lodging (long-term) in San Francisco over time (different snapshots) from February 2017 to June 2019. The three vertical lines regard the timing of the Settlement Agreement between the San Francisco City Council and Airbnb. The agreement was signed in May 2017 and it has been effective since September 2017. According to the resolution, from January 2018 all eligible Airbnb listings should be registered.

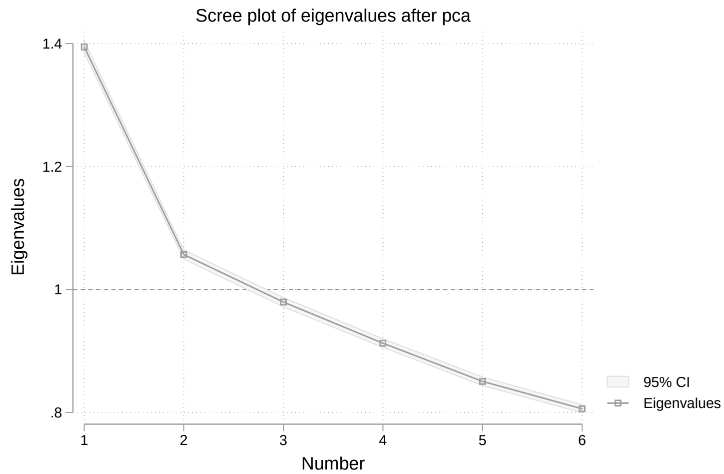
Table A.1: Summary Statistics: the Settlement Agreement and Listings Selection in September 2017.

	Group C		Group D			
	Mean	SD	Mean	SD	Δ	$p-value$
Days in Airbnb	1,054.5	388.5	570.9	242.8	483.5	0.0
Days in Airbnb before September 2017	524.4	286.2	493.4	247.9	30.3	0.0
Total number of reviews	45.5	61.4	9.8	24.4	35.1	0.0
Price per night	206.4	165.0	246.0	232.4	-39.6	0.0
Availability next 30 days	7.1	8.7	3.5	8.4	3.5	0.0
Average rating per snapshot: overall	94.3	6.0	93.1	8.9	1.3	0.0
Average rating per snapshot: accuracy	9.6	0.6	9.4	0.9	0.1	0.0
Average rating per snapshot: check-in	9.8	0.5	9.6	0.6	0.1	0.0
Average rating per snapshot: cleanliness	9.5	0.7	9.2	1.19	0.3	0.0
Average rating per snapshot: communication	9.8	0.5	9.7	0.80	0.9	0.0
Average rating per snapshot: location	9.5	0.6	9.4	0.9	0.08	0.00
Average rating per snapshot: value-for-money	9.2	0.7	9.1	1.5	0.9	0.00
Minimum nights required	5.5	10.0	3.0	4.6	2.4	0.0
No short-term rentals	10%	-	1%	-	0.08	-
Registration displayed or not required	20%	-	3%	-	0.16	-
Number of listings	4,560	-	3,642	-	-	-

Note: The table compare the profile of listings before and after the Settlement Agreement. All the statistics refer to the snapshot regarding September 2017. Listings are divided in two groups: Group C contains all listings who enter the platform before September 2017 and exit after January 2018, when the implementation of the Settlement Agreement was completed. Group D contains all listings who enter the platform before September 2017 and exit before January 2018. The last two columns provide the differences between the statistics' averages and the $p-value$ of the difference. The numbers of listings in the two groups are not equal to the ones shown in Table 1.2 since not all listings in the two groups were active (present on the platform) at the date of the snapshot regarding September 2017.

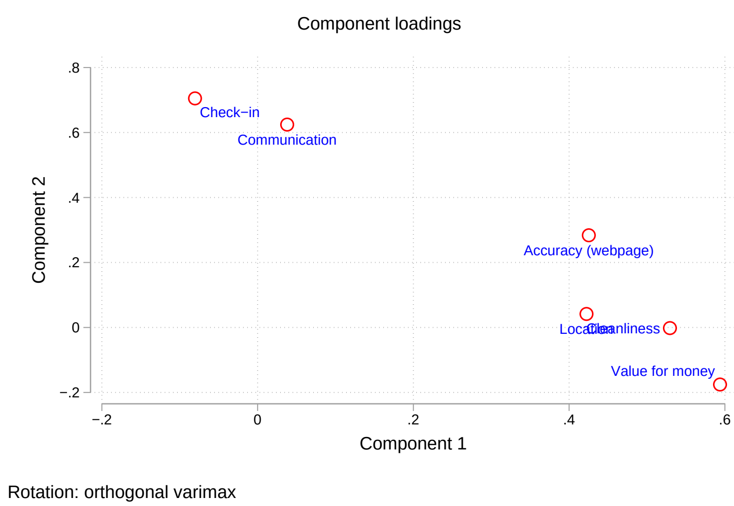
1.11 Appendix: Identification Strategy

Figure A.2: (PCA) Screeplot for the Components of All Rating Categories



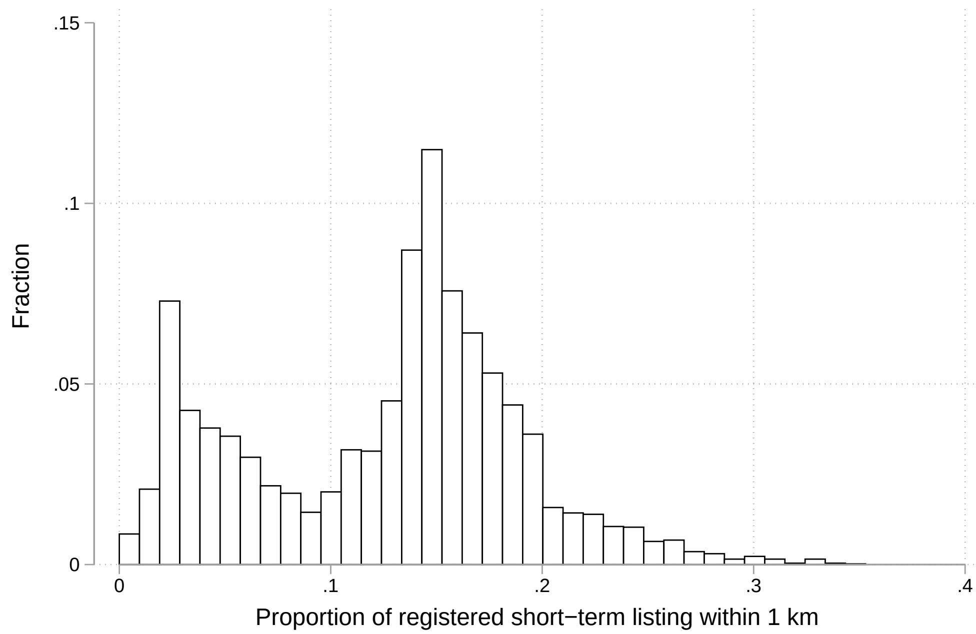
Note: The figure plots the eigenvalues of all principal components of all the rating per snapshot of all the categories. Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. Only the first two components have to be retained following the rule to use only components whose eigenvalue is greater than one.

Figure A.3: (PCA) Loading of All Rating Categories over the First Two Components



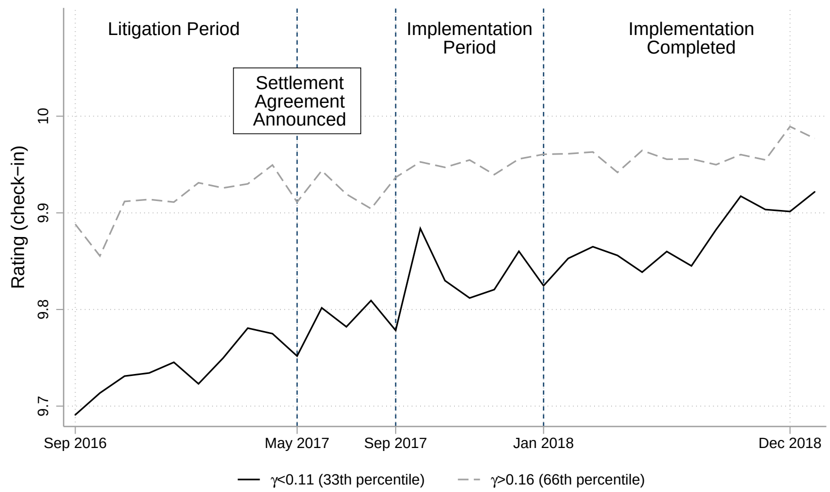
Note: The figure plots the varimax rotated loadings over the first two components of a PCA performed over the rating per snapshot of all the categories. Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. The ratings are all very correlated and the first component already explain more than 30 percent of the ratings variations. Ratings regarding check-in and communication correlate the most and their loadings are distant from all the others. Conversely, all the other dimensions tend to have similar loadings. These results are robust to promax rotation.

Figure A.4: Distribution of γ_i^1



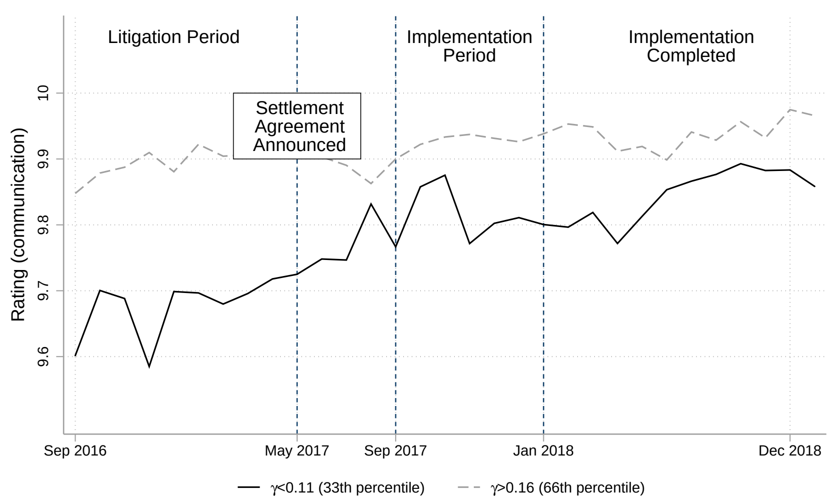
Note: The figure shows the distribution of values of γ_i^1 for the set of listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 (Group C in Section 1.3.4).

Figure A.5: Evolution of $\bar{r}_{i,t}^{check-in}$ for Different Groups of Listings



Note: The figure plots the average values of $\bar{r}_{i,t}^{check-in}$) for two different groups of listings. The solid line represents $\bar{r}_{i,t}^{check-in}$ for those listings with $\gamma_i^1 \leq 0.12$; whereas the dotted line represents $\bar{r}_{i,t}^{check-in}$ for those listings with $\gamma_i^1 \geq 0.16$. Only listings offering short-term lodging that enter before September 2017 and exit after January 2018 are considered. Listings represented by the solid line are predicted to be the most affected by the Settlement Agreement; whereas listings represented by the dotted line are predicted to be the least affected.

Figure A.6: Evolution of $\bar{r}_{i,t}^{comm}$ for Different Groups of Listings



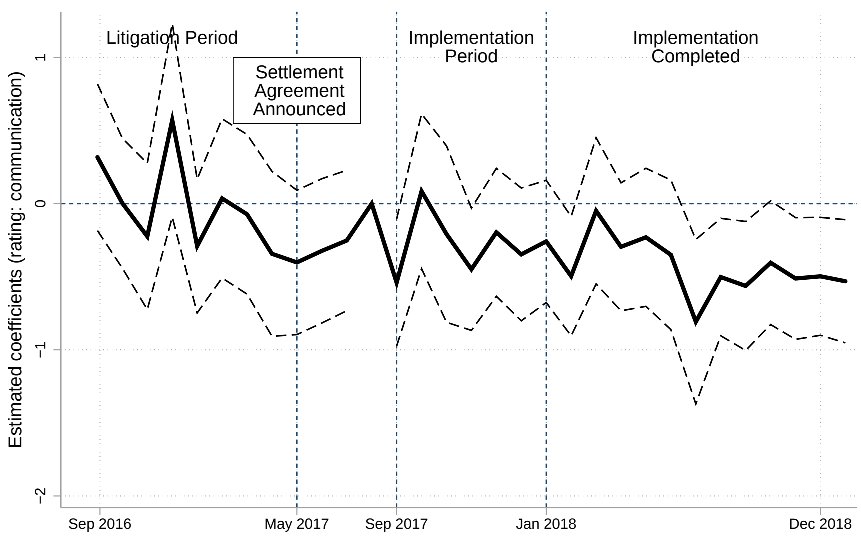
Note: The figure plots the average values of $\bar{r}_{i,t}^{comm}$ for two different groups of listings. The solid line represents $\bar{r}_{i,t}^{comm}$ for those listings with $\gamma_i^1 \leq 0.12$; whereas the dotted line represents $\bar{r}_{i,t}^{comm}$ for those listings with $\gamma_i^1 \geq 0.16$. Only listings offering short-term lodging that enter before September 2017 and exit after January 2018 are considered. Listings represented by the solid line are predicted to be the most affected by the Settlement Agreement; whereas listings represented by the dotted line are predicted to be the least affected.

Table A.2: Impact of the Settlement Agreement on Competition (First Stage) - Neighborhood Clustered and Robust s.e.

	$\ln(L^{0.5}_{i,t})$ (1)	$\ln(L^{1}_{i,t})$ (2)	$\ln(L^{2}_{i,t})$ (3)	$\ln(L^{0.5}_{i,t})$ (4)	$\ln(L^{1}_{i,t})$ (5)	$\ln(L^{2}_{i,t})$ (6)
$\gamma_i^{0.5} \times post_{Nov2017}$	1.497***			1.497***		
	[0.305]			[0.0819]		
$\gamma_i^{1} \times post_{Nov2017}$		2.477***			2.477***	
		[0.458]			[0.0804]	
$\gamma_i^{2} \times post_{Nov2017}$			3.222***			3.222***
			[0.280]			[0.0443]
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	4.227	5.488	6.737	4.227	5.488	6.737
F-test	24.00	41.66	196.64	663.3	1467.9	4023.8
R^2	0.74	0.85	0.93	0.74	0.85	0.93
N	57,323	57,330	57,344	57,323	57,330	57,344

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. In Columns (1), (2), and (3) standard errors clustered by neighborhood are in parentheses. In San Francisco there are 36 neighborhoods. In Columns (4), (5), and (6) robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A.7: Estimated Coefficients from Equation 1.4.4: Ratings Regarding Communication



Note: In line with Equation 1.4.4, $\bar{r}^{comm}_{i,t}$ is regressed on listing and snapshot fixed effects, and on the products between γ_i^j and snapshot dummies. Standard errors are clustered by listing. The graph plots the estimated coefficients on these products. The value of the coefficient corresponding to August 2017 ($\hat{\beta}_{Aug2017}$) is normalized to zero. Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered.

1.12 Appendix: Main Results

Table A.3: OLS Estimates of the Impact of Competition on Hosts' Effort - Conley s.e.

	$\bar{r}_{i,t}^{check-in}$			$\bar{r}_{i,t}^{comm}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(L_{i,t}^{0.5})$	-0.0077			-0.0016		
	[0.008]			[0.006]		
$\ln(L_{i,t}^{1})$		-0.022**			-0.013	
		[0.010]			[0.0091]	
$\ln(L_{i,t}^{2})$			-0.036**			-0.010
			[0.016]			[0.013]
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	9.900	9.900	9.900	9.879	9.879	9.879
R^2	0.431	0.431	0.431	0.498	0.498	0.498
N	57,274	57,274	57,274	57,274	57,274	57,274

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. Standard errors (in parentheses) are adjusted to reflect spatial dependence as in Conley (1999). Spatial autocorrelation is assumed to linearly decrease in distance up to a cutoff of 10 km (covering all San Francisco municipality). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4: OLS Estimates of the Impact of Competition on Hosts' Effort - Neighborhood Clustered s.e.

	$\bar{r}_{i,t}^{check-in}$			$\bar{r}_{i,t}^{comm}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(L_{i,t}^{0.5})$	-0.0077			-0.0016		
	[0.013]			[0.013]		
$\ln(L_{i,t}^{1})$		-0.022			-0.012	
		[0.019]			[0.016]	
$\ln(L_{i,t}^{2})$			-0.036			-0.010
			[0.033]			[0.029]
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	9.900	9.900	9.900	9.879	9.879	9.879
R^2	0.0055	0.0042	0.0024	0.0058	0.005	9.0043
N	57,323	57,330	57,344	57,323	57,330	57,344

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. Standard errors clustered by neighborhood are in parentheses. In San Francisco there are 36 neighborhoods. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5: OLS Estimates of the Impact of Competition on Hosts' Effort - Robust s.e.

	$\bar{r}_{i,t}^{check-in}$			$\bar{r}_{i,t}^{comm}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(L_{i,t}^{0.5})$	-0.0077			-0.0016		
	[0.012]			[0.011]		
$\ln(L_{i,t}^{1})$		-0.022			-0.012	
		[0.016]			[0.016]	
$\ln(L_{i,t}^{2})$			-0.036			-0.010
			[0.022]			[0.022]
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	9.900	9.900	9.900	9.879	9.879	9.879
R^2	0.0055	0.0042	0.0024	0.0058	0.0049	0.0043
N	57,323	57,330	57,344	57,323	57,330	57,344

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.6: Impact of the Settlement Agreement on Hosts' Effort (Reduced Form) - Conley s.e.

	$\bar{r}_{i,t}^{check-in}$			$\bar{r}_{i,t}^{comm}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\gamma_i^{0.5} \times post_{Nov2017}$	-0.183***			-0.158***		
	[0.0443]			[0.0465]		
$\gamma_i^{1} \times post_{Nov2017}$		-0.272***			-0.267***	
		[0.0643]			[0.0818]	
$\gamma_i^{2} \times post_{Nov2017}$			-0.316***			-0.259***
			[0.0830]			[0.0954]
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	9.900	9.900	9.900	9.879	9.879	9.879
R^2	0.0023	0.0018	0.0020	0.0028	0.0022	0.0030
N	57,323	57,330	57,344	57,323	57,330	57,344

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. Standard errors (in parentheses) are adjusted to reflect spatial dependence as in Conley (1999). Spatial autocorrelation is assumed to linearly decrease in distance up to a cutoff of 10 km (covering all San Francisco municipality). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.7: Impact of the Settlement Agreement on Hosts' Effort (Reduced Form) - Neighborhood Clustered s.e.

	$\bar{r}_{i,t}^{check-in}$			$\bar{r}_{i,t}^{comm}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\gamma_i^{0.5} \times post_{Nov2017}$	-0.183*			-0.158*		
	[0.104]			[0.0935]		
$\gamma_i^{1} \times post_{Nov2017}$		-0.272*			-0.267*	
		[0.157]			[0.147]	
$\gamma_i^{2} \times post_{Nov2017}$			-0.316			-0.259
			[0.188]			[0.171]
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	9.900	9.900	9.900	9.879	9.879	9.879
R^2	0.0023	0.0018	0.0020	0.0028	0.0022	0.0030
N	57,323	57,330	57,344	57,323	57,330	57,344

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. Standard errors clustered by neighborhood are in parentheses. In San Francisco there are 36 neighborhoods. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.8: Impact of the Settlement Agreement on Hosts' Effort (Reduced Form) -Robust s.e.

	$\bar{r}^{check-in}_{i,t}$			$\bar{r}^{comm}_{i,t}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\gamma_i^{0.5} \times post_{Nov2017}$	-0.183***			-0.158***		
	[0.0647]			[0.0608]		
$\gamma_i^{1} \times post_{Nov2017}$		-0.272***			-0.267***	
		[0.0960]			[0.0872]	
$\gamma_i^{2} \times post_{Nov2017}$			-0.316***			-0.259**
			[0.115]			[0.102]
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	9.900	9.900	9.900	9.879	9.879	9.879
R^2	0.0023	0.0018	0.0020	0.0028	0.0022	0.0030
N	57,323	57,330	57,344	57,323	57,330	57,344

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.9: IV Estimates of the Impact of Competition on Hosts' Effort - Conley s.e.

	$\bar{r}^{check-in}_{i,t}$			$\bar{r}^{comm}_{i,t}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(L^{0.5}_{i,t})$	-0.122***			-0.106***		
	[0.0291]			[0.0320]		
$\ln(L^{1}_{i,t})$		-0.110***			-0.108***	
		[0.0259]			[0.0342]	
$\ln(L^{2}_{i,t})$			-0.0982***			-0.0804***
			[0.0255]			[0.0305]
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	9.900	9.900	9.900	9.879	9.879	9.879
R^2	0.0022	0.0011	0.00062	0.0024	0.00068	0.00017
N	57,323	57,330	57,344	57,323	57,330	57,344

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. Standard errors (in parentheses) are adjusted to reflect spatial dependence as in Conley (1999). Spatial autocorrelation is assumed to linearly decrease in distance up to a cutoff of 10 km (covering all San Francisco municipality). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.10: IV Estimates of the Impact of Competition on Hosts' Effort - Neighborhood Clustered s.e.

	$\bar{r}_{i,t}^{check-in}$			$\bar{r}_{i,t}^{comm}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(L_{i,t}^{0.5})$	-0.122			-0.106		
	[0.0829]			[0.0740]		
$\ln(L_{i,t}^{1})$		-0.110			-0.108	
		[0.0699]			[0.0674]	
$\ln(L_{i,t}^{2})$			-0.0982*			-0.0804
			[0.0587]			[0.0541]
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	9.900	9.900	9.900	9.879	9.879	9.879
R^2	0.0022	0.0011	0.00062	0.0024	0.00068	0.00017
N	57,323	57,330	57,344	57,323	57,330	57,344

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. Standard errors clustered by neighborhood are in parentheses. In San Francisco there are 36 neighborhoods. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.11: IV Estimates of the Impact of Competition on Hosts' Effort - Robust s.e

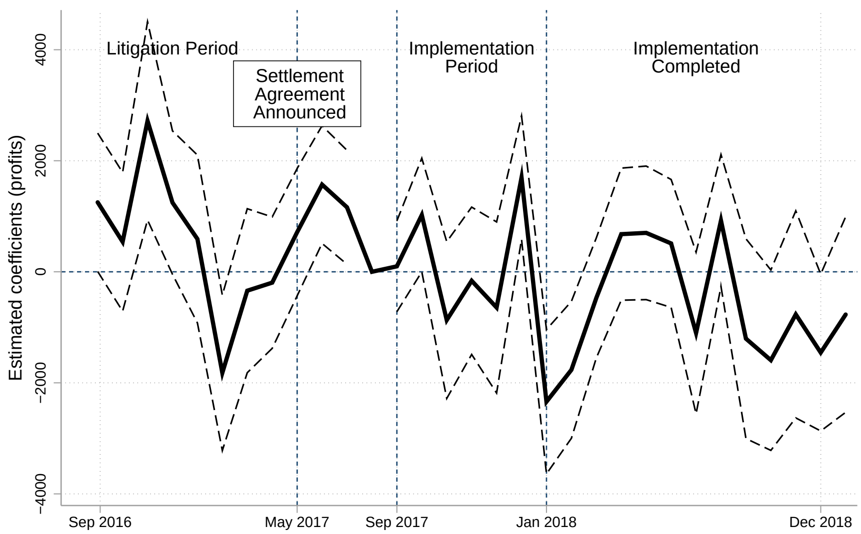
	$\bar{r}_{i,t}^{check-in}$			$\bar{r}_{i,t}^{comm}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(L_{i,t}^{0.5})$	-0.122***			-0.106**		
	[0.0438]			[0.0412]		
$\ln(L_{i,t}^{1})$		-0.110***			-0.108***	
		[0.0389]			[0.0354]	
$\ln(L_{i,t}^{2})$			-0.0982***			-0.0804**
			[0.0357]			[0.0318]
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	9.900	9.900	9.900	9.879	9.879	9.879
R^2	0.0022	0.0011	0.00062	0.0024	0.00068	0.00017
N	57,323	57,330	57,344	57,323	57,330	57,344

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

1.13 Appendix: Extensions and Robustness Checks

1.13.1 Competition and Profits

Figure A.8: Estimated Coefficients from Equation 1.6.1: Profits



Note: In line with Equation 1.6.1, $\pi_{i,t}$ is regressed on listing and snapshot fixed effects, and on the products between γ_i^1 and snapshot dummies. Standard errors are clustered by listing. The graph plots the estimated coefficients on these products. The value of the coefficient corresponding to August 2017 ($\hat{\beta}_{Aug2017}$) is normalized to zero. Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered.

Table A.12: OLS Estimates of the Impact of Competition on the Estimated Hosts' Effort

	$e_{i,t}^{check-in}$			$e_{i,t}^{comm}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(L_{i,t}^{0.5})\times 10$	-0.0612			-0.0172		
	[0.123]			[0.117]		
$\ln(L_{i,t}^{1})\times 10$		-0.187			-0.127	
		[0.164]			[0.165]	
$\ln(L_{i,t}^{2})\times 10$			-0.323			-0.0574
			[0.223]			[0.228]
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	0.0063	0.0063	0.0063	0.0072	0.0072	0.0072
R-squared	0.0032	0.0032	0.0032	0.0032	0.0032	0.0031
N	55,633	55,640	55,654	55,633	55,640	55,654

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. Standard errors clustered by listing are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

1.13.2 Effort Estimation

The effort estimation presented in Section 1.6 relies on a relationship between guests' characteristics regarding different features of the same lodging service. In particular, Equation 1.7.3 assumes a linear model between $guest_{i,t}^{effort}$ and $guest_{i,t}^{location}$ for all Airbnb guests in the dataset (up to the error term $\epsilon_{i,t}$).

Still, the relationship between guests' perception for the components of hosts' services may be heterogeneous for different types of guests; and the assumption of Equation 1.7.3 may be partially relaxed to account for such heterogeneity. The control function approach derived in Equation 1.7.4 relies on the assumption that host's effort $e_{i,t}$ can be identified looking at time variations of ratings $\bar{r}_{i,t}^{effort}$ after removing the trend due to the correlation with $\bar{r}_{i,t}^{location}$. Accordingly, this estimation technique cannot allow for time varying parameters affecting the linear relationship between the two ratings: i.e. α and β cannot vary over time. Still, the guests' perception for the components of hosts' services may differ for specific time-invariant groups of listings. In particular, it is possible to substitute the assumption in Equation 1.7.3 with the following two-stage formulation in which the parameters α and β differ for each group n:

$$guest_{i,t}^{effort} = \alpha_n + \beta_n guest_{i,t}^{location} + \epsilon_{i,t} \tag{1.13.1}$$

$$\alpha_n = \alpha + v_n \tag{1.13.2}$$

$$\beta_n = \beta + u_n, \tag{1.13.3}$$

where v_n and u_n are the random effect and coefficient varying for each group n. In line with the approach used in Section 1.6, I derive the following panel regression:

$$\bar{r}_{i,t}^{effort} = \alpha_n - \beta_n\theta_i + \beta_n\bar{r}_{i,t}^{location} + e_{i,t} + \epsilon_{i,t}. \tag{1.13.4}$$

The main difference between Equation 1.7.4 and 1.13.4 regards the coefficients α_n and β_n that vary for different groups. Yet, Equation 1.13.4 can be simplified operating a within transformation to account for the listing fixed effect due to the fixed characteristics θ_i:

$$(\bar{r}_{i,t}^{effort} - \bar{\bar{r}}_{i}^{effort}) = \beta_n(\bar{r}_{i,t}^{location} - \bar{\bar{r}}_{i}^{location}) + (e_{i,t} - \bar{e}_i) + (\epsilon_{i,t} - \bar{\epsilon}_i) \tag{1.13.5}$$

$$(\bar{r}_{i,t}^{effort} - \bar{\bar{r}}_{i}^{effort}) = \beta(\bar{r}_{i,t}^{location} - \bar{\bar{r}}_{i}^{location}) \tag{1.13.6}$$

$$+ u_n(\bar{r}_{i,t}^{location} - \bar{\bar{r}}_{i}^{location}) + (e_{i,t} - \bar{e}_i) + (\epsilon_{i,t} - \bar{\epsilon}_i), \tag{1.13.7}$$

where $\bar{\bar{r}}_{i}^{effort}$ and $\bar{\bar{r}}_{i}^{location}$ are the listing average ratings per snapshot regarding effort and location, respectively.

The within formulation of the panel regression removes the fixed part of the model $\alpha_n - \beta_n\theta_i$ and only the random coefficient u_n remains to capture the heterogeneous relationship between $guest_{i,t}^{effort}$ and $guest_{i,t}^{location}$. Treating u_n as random implies the necessity to have further assumptions about the distribution of the random effect and its independence. In particular, the following assumptions need to hold:

$$E[e_{i,t}u_n|\theta_i] = 0 \tag{OC_3}$$

$$E[\epsilon_{i,t}u_n|\theta_i] = 0 \tag{OC_4}$$

$$E[\bar{r}_{i,t}^{location}u_n|\theta_i] = 0, \tag{OC_5}$$

with $u_n \sim \mathcal{N}(0, \sigma_u^2)$. In this sense, hosts are assumed to not respond to changes in u_n with variations in effort; and u_n is assumed to not be correlated with variations in the rating regarding location.

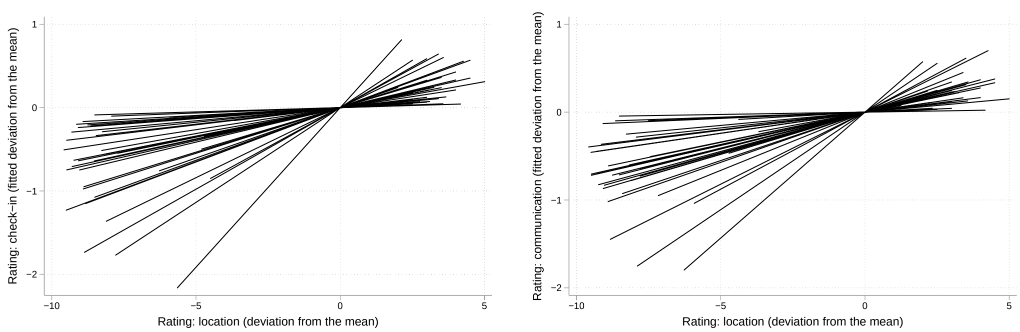
Different time-invariant groups can be used to add heterogeneity in the relationship between guests' characteristics. Here I use the thirty-seven neighborhoods in the San Francisco city center to capture the different profile of guests using Airbnb in the city. In certain neighborhoods, tourists may give extra importance to listings' location; whereas other areas may attract guests with different tastes and priorities. Table A.13 shows the results about the panel fixed effect regression in Equation 1.7.4 and 1.13.4 for the ratings regarding check-in and communication. The values of β are positive and significant in all cases. This is in line with the assumption of the relationship between the ratings regarding effort and location. Moreover, the Likelihood Ratio test at the bottom of the table shows that the hypothesis of $\sigma_u^2 = 0$ (equivalent to $u_n = 0\ \forall n$) is rejected suggesting that the random slope for each neighborhood improves the predictive power of the model. In line with this result, Figure A.9 shows how the slopes β_n vary for different neighborhoods. In particular, the two graphs plot the fitted values of $(\bar{r}_{i,t}^{effort} - \bar{\bar{r}}_{i}^{effort})$ over $(\bar{r}_{i,t}^{location} - \bar{\bar{r}}_{i}^{location})$ using the estimated β and u_n. Other specifications with a wider range of random effects are possible. Still, adding further heterogeneity does not seem to improve the power of the model: when other time-invariant heterogeneity is added (such as the types of rented property) the Likelihood Ratio test shows that the other sources of heterogeneity do not improve the model's predictive power.

Table A.13: Relationship between Guests' Characteristics

	$\bar{r}_{i,t}^{check-in}$		$\bar{r}_{i,t}^{comm}$	
	(1)	(2)	(3)	(4)
$\bar{r}_{i,t}^{location}$	0.0758***	0.0865***	0.0774***	0.0836***
	[0.00219]	[0.0134]	[0.00217]	[0.0113]
u_n		0.0768***		0.0643***
		[0.0108]		[0.00919]
Listing FE	✓	✓	✓	✓
LR test vs. linear model		392.89		275.33
N	120,905	120,905	121,017	121,017

Note: Standard errors clustered by listing are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A.9: Relationship between Guests' Characteristics in Different Neighborhoods



Note: The graphs plots the estimated random coefficients u_n for different neighborhoods. As observed in Table A.13, the relationship between guests' characteristics (effort and location) significantly vary among neighborhoods.

I use the residuals obtained from Equation 1.13.4 as a new measure of host's effort. Repeating the analysis described in Section 1.6, I get qualitatively similar results. In particular, I regress the variable hosts' response rate over the effort measures $e_{i,t}^{check}$, $e_{i,t}^{comm}$, and the location rating $\bar{r}_{i,t}^{location}$ controlling for listing fixed effects (see Table A.14). As for the previous estimates of the host's effort, the results support condition OC_2: hosts' response rate is positively and significantly correlated with the effort dimensions. Finally, I replicate again the identification strategy in Section 1.4 using the new estimates of $e_{i,t}^{check}$ and $e_{i,t}^{comm}$. Table A.15 reports the IV estimates. Again a negative relationship between the number of competitors and hosts' effort is present and it holds even after allowing for neighborhood-specific trends.

Table A.14: Evidence Supporting Assumption OC_5: Response Rate, $\bar{r}^{location}_{i,t}$, $e_{i,t}$

	Response rate	Response rate	Response rate
$\bar{r}^{location}_{i,t} \times 100$	0.0661		
	[0.0499]		
$e^{comm}_{i,t} \times 100$		0.212**	
		[0.107]	
$e^{check}_{i,t} \times 100$			0.310***
			[0.112]
Listing FE	✓	✓	✓
Mean	0.973	0.974	0.974
R-squared	0.000052	0.00022	0.00056
N	50,432	49,650	49,615

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. Standard errors clustered by listing are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.15: IV Estimates of the Impact of Competition on the Estimated Hosts' Effort

	$e^{check-in}_{i,t}$			$e^{comm}_{i,t}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(L^{0.5}_{i,t}) \times 10$	-0.923**			-0.678*		
	[0.427]			[0.402]		
$\ln(L^{1}_{i,t}) \times 10$		-0.807**			-0.700**	
		[0.381]			[0.344]	
$\ln(L^{2}_{i,t}) \times 10$			-0690**			-0.456
			[0.352]			[0.313]
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	0.006	0.006	0.006	0.007	0.007	0.007
R^2	0.00012	0.00019	0.00036	0.00014	0.00018	0.00059
N	55,633	55,640	55,654	55,633	55,640	55,654

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. Standard errors clustered by listing are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.16: OLS Estimates of the Impact of Competition on Hosts' Effort Controlling for Composition

	$\bar{r}^{check-in}_{i,t}$			$\bar{r}^{comm}_{i,t}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(L^{0.5}_{i,t})$	-0.0133			0.0141		
	[0.0179]			[0.0167]		
$\ln(L^{1}_{i,t})$		-0.0206			0.00215	
		[0.0197]			[0.0193]	
$\ln(L^{2}_{i,t})$			-0.0208			0.0251
			[0.0321]			[0.0315]
$\boldsymbol{X_{i,t}}$	✓	✓	✓	✓	✓	✓
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	9.898	9.900	9.900	9.879	9.879	9.879
R^2	0.0056	0.0050	0.0050	0.0051	0.0048	0.0047
N	47,070	54,610	57,170	47,070	54,610	57,170

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. $\boldsymbol{X_{i,t}}$ includes $z^{j,shared}_{i,t}$, $z^{j,super}_{i,t}$, $z^{j,90/100}_{i,t}$, $z^{j,90-100/100}_{i,t}$, $z^{j,acc1/5}_{i,t}$, $z^{j,acc2/5}_{i,t}$, and $z^{j,acc3-4/5}_{i,t}$ where the distance j corresponds to the one used for the main independent variable. Standard errors clustered by listing are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.17: Impact of the Settlement Agreement on Competition Controlling for Composition (First Stage)

	$\ln(L^{0.5}_{i,t})$	$\ln(L^{1}_{i,t})$	$\ln(L^{2}_{i,t})$
$\gamma^{0.5}_i \times post_{Nov2017}$	1.692***		
	[0.0687]		
$\gamma^{1}_i \times post_{Nov2017}$		2.009***	
		[0.0850]	
$\gamma^{2}_i \times post_{Nov2017}$			1.678***
			[0.0567]
$\boldsymbol{X_{i,t}}$	✓	✓	✓
Listing FE	✓	✓	
Snap FE	✓	✓	✓
Mean	4.472	5.563	6.745
F-test	780	1,713	7,930
R^2	0.0875	0.160	0.251
N	47,070	54,610	57,170

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. $\boldsymbol{X_{i,t}}$ includes $z^{j,shared}_{i,t}$, $z^{j,super}_{i,t}$, $z^{j,90/100}_{i,t}$, $z^{j,90-100/100}_{i,t}$, $z^{j,acc1/5}_{i,t}$, $z^{j,acc2/5}_{i,t}$, and $z^{j,acc3-4/5}_{i,t}$ where the distance j corresponds to the one used for the main independent variable. Standard errors clustered by listing are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.18: Impact of the Settlement Agreement on Hosts' Effort Controlling for Composition (Reduced Form)

	$\bar{r}_{i,t}^{check-in}$			$\bar{r}_{i,t}^{comm}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\gamma_i^{0.5} \times post_{Nov2017}$	-0.245***			-0.162**		
	[0.0746]			[0.0725]		
$\gamma_i^{1} \times post_{Nov2017}$		-0.236**			-0.245**	
		[0.110]			[0.101]	
$\gamma_i^{2} \times post_{Nov2017}$			-0.212			-0.213
			[0.167]			[0.141]
$\boldsymbol{X_{i,t}}$	✓	✓	✓	✓	✓	✓
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	9.898	9.900	9.900	9.879	9.879	9.879
R^2	0.00596	0.00518	0.00501	0.00530	0.00499	0.00479
N	47,070	54,610	57,170	47,070	54,610	57,170

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. $\boldsymbol{X_{i,t}}$ includes $z_{i,t}^{j,shared}$, $z_{i,t}^{j,super}$, $z_{i,t}^{j,90/100}$, $z_{i,t}^{j,90-100/100}$, $z_{i,t}^{j,acc1/5}$, $z_{i,t}^{j,acc2/5}$, and $z_{i,t}^{j,acc3-4/5}$ where the distance j corresponds to the one used for the main independent variable. Standard errors clustered by listing are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.19: IV Estimates of the Impact of Competition on Hosts' Effort Controlling for Composition

	$\bar{r}_{i,t}^{check-in}$			$\bar{r}_{i,t}^{comm}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(L_{i,t}^{0.5})$	-0.145***			-0.0959**		
	[0.0447]			[0.0432]		
$\ln(L_{i,t}^{1})$		-0.118**			-0.122**	
		[0.0553]			[0.0509]	
$\ln(L_{i,t}^{2})$			-0.127			-0.127
			[0.0999]			[0.0838]
$\boldsymbol{X_{i,t}}$	✓	✓	✓	✓	✓	✓
Listing FE	✓	✓	✓	✓	✓	✓
Snap FE	✓	✓	✓	✓	✓	✓
Mean	9.898	9.900	9.900	9.879	9.879	9.879
R^2	0.00216	0.000165	0.000284	0.00206	0.0000799	0.0000289
N	47,070	54,610	57,170	47,070	54,610	57,170

Note: Only listings offering short-term lodging that enter the platform before September 2017 and exit after January 2018 are considered. $\boldsymbol{X_{i,t}}$ includes $z_{i,t}^{j,shared}$, $z_{i,t}^{j,super}$, $z_{i,t}^{j,90/100}$, $z_{i,t}^{j,90-100/100}$, $z_{i,t}^{j,acc1/5}$, $z_{i,t}^{j,acc2/5}$, and $z_{i,t}^{j,acc3-4/5}$ where the distance j corresponds to the one used for the main independent variable. Standard errors clustered by listing are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Chapter 2

Quality Disclosures and Disappointment: Evidence from the Academy Awards

2.1 Introduction

Certifications, and in general, third-party quality disclosures are often used in markets with asymmetries of information. In these circumstances, buyers are not perfectly informed about the seller's quality. Thus, a third-party certification may help reducing the uncertainty on the buyers' side and increase their willingness to pay: used cars' sellers may show the most recent inspections by the car's manufacturer to assure prospective buyers about the good state of the car. The positive effect of quality disclosure has already been studied in many contexts affected by asymmetric information: Dranove and Jin (2010) provide a complete review of the power (and the limitations) of these tools to provide a credible signal for sellers' quality. When a certifier is credible, a third-party disclosure can effectively increase buyers' expectations and attract high-quality sellers to trade.

Still, altering buyers' expectations could have unexpected side-effects when buyers' utility depends on reference points induced by their expectations. According to the framework of reference-dependent preferences pioneered by the seminal paper by Kahneman and Tversky (1979), agents' reference points affect their utility throughout a "gain/loss" component which describes their perception of elation or disappointment. The role of agents' expectations to explain reference point formation received the attention by many scholars from a theoretical perspective (Loomes and Sugden, 1982; Bell, 1983; Koszegi and Rabin, 2006). Empirical evidence suggests that expectation-dependent preferences effectively describe agents' behavior in different settings (Camerer et al., 2002; Crawford and Meng, 2009; Card and Dahl, 2011; Bartling et al., 2012; Backus et al., 2017). Accordingly, disclosures by third-parties improving buyers' expectations on sellers' quality may increase the chances of buyers' disappointment and reduce the benefits of lower informational asymmetries.

This paper empirically identifies the disappointment effect due to quality disclosures estimating the causal impact of the nominations for the Academy of Motion Picture Arts and

Sciences (AMPAS) awards on movie ratings. Nominations constitute the "shifter" of reference point about the movies' quality; whereas the variations of ratings displayed on an online movie recommender system (MovieLens) provide a measure for the disappointment effect. My findings show that, after nominations, ratings for nominated movies significantly drop relative to ratings for not nominated movies with similar characteristics. In particular, the drop in ratings due to disappointment accounts for more than 5 percent of the rating premium for nominated movies.

This empirical exercise may help to shed light on the welfare impact of quality disclosures in a setting of asymmetry of information and expectation-dependent preferences. With this work, I do not question the positive impact of certifications and awards on sellers' performance. Still, here I document that quality disclosures also produce a depressing effects on buyers' satisfaction (ratings) due to disappointment. This latter effect may reduce the positive effects of certifications. Yet, quantifying the decrease in profits due to disappointment is out of the scope of this article.

The specific context of analysis presents advantages and limitations. The main advantage regards the absence of variations in prices charged by movie theaters before and after the Academy Awards nominations. Accordingly, by looking at differences in ratings, disappointment is identified and its effect is not influenced by changes in prices. In general, this is not the case for sellers who receive a certification: given the increase in buyers' willingness to pay due to the certification, sellers may adjust and charge a higher price. Empirically, variations in prices are problematic since the disappointment effect could not be disentangled from a reduction in the buyers' utility due to a higher price.[1] The main challenge for the identification of the disappointment effect through the ratings' variation regards the selection of moviegoers who watch and rate the movie before or after the nomination. Due to the "quality disclosure" provided by the nomination, a different profile of moviegoers watches and rates movies. Thus, the variations in the ratings may depend on differences in tastes or preferences.

In this paper, first, I identify the impact of the AMPAS nominations on ratings of nominated movies with a difference-in-difference design (DiD). The results show a negative and significant drop in ratings for nominated movies after nomination relative to not nominated movies rated in the same periods. This identification procedure does not entirely disentangle selection from disappointment. Then, I present a second identification strategy to account for the selection of moviegoers. Here the response variable is the difference in ratings reported by the same individual for a couple of movies: a nominated movie and a not nominated movie that share several common features such as the genre. I show that, studying the variations of this difference, I can reduce the impact of selection on the ratings' variations over time and identify the disappointment effect.

The results for both designs show a negative and significant drop in ratings for nominated movies after nominations. This is in line with expectation-dependent preferences lowering down moviegoers' perceived utility after an upward shift in the expectations. Because of disappointment, the gap between nominated and not nominated movies reduces by more than 5 percent in the 30 days after a nomination. In particular, the negative effect is stronger once I try to

[1]Elfenbein et al. (2015) show that eBay sellers charge significantly higher prices after receiving the eBay's "top-rated seller" certification.

isolate disappointment in the second identification.

The implications of these results are relevant for the design of third-party quality disclosures and certifications in many contexts with informational asymmetries. With this study, I do not intend to question the efficacy of these tools to reduce buyers' uncertainty. Yet, here I show that a lower degree of uncertainty may not correspond to a higher level of ex-post buyers' utility. This may be of special interest for sellers of experience goods, such as movie producers. They should be aware that quality disclosures such as awards may generate unrealistic expectations and foster disappointment on the buyers' side.

The paper proceeds as follows. Section 2.2 describes the literature review. In Section 2.3, I provide some background context regarding the platform of movie recommendations MovieLens, and its rating process; then, I present the dataset. This is followed by a short theoretical framework in Section 2.4. I discuss my identification strategy in Section 2.5. Section 2.6 provides the empirical findings. Section 2.7 concludes. Additional tables, figures and extensions of the results are in Appendix.

2.2 Literature Review

This paper contributes to the literature regarding quality disclosures, reference-dependent preferences, and online reviews. Moreover, from an econometric perspective, the identification designs exposed in this work combine machine learning tools with more standard microeconometric techniques. As it is suggested by Athey and Imbens (2019), the interconnections between these new techniques and more classical approaches could lead to effective solutions. With this work, I show an example of such integration using unsupervised learning techniques (k-mean and k-median cluster analyses). I use these algorithms to cluster movies with similar features, and to refine the control group of not nominated movies used to estimate the counterfactual movements of ratings for nominated ones.

The literature about quality disclosures has focused on the impact of these devices to improve sellers' performances and market outcomes. Jin and Leslie (2003) show that the introduction of restaurant hygiene report cards reduced food-related illnesses in Los Angeles with cleaner establishments attracting more consumers. Similarly, Chezum and Wimmer (2003) document a positive effect of certifications for racehorses in terms of higher prices and better racing performances. For what concerns digital platforms, Elfenbein et al. (2015), Hui et al. (2016b), and Hui et al. (2018) study the role of certification programs in eBay and they report positive effects over seller's quality. Conversely, in an online platform for residential home services, Farronato et al. (2020) observe that professionals showing their licensing status do not increase their number of transactions or charge higher prices. For what concerns the AMPAS awards, several articles (Nelson and Donihue, 2001; McKenzie, 2012) document their positive impact on movies' box office; still, up to my knowledge, the effect of these awards on users' ratings has never been studied.

Few papers try to investigate the adverse effects of quality disclosures: Dranove et al. (2003) show that after a hospital "Report Card" program was introduced in New York, hospitals started to avoid potential low grades declining to treat more "difficult" patients affected by severe diseases. Ho (2012) describes several flaws of the US restaurant hygiene system showing inflation in grades and a shift of inspection resources to resolve disputes in grading. Finally, Forbes et al. (2015) investigate how a disclosure program for airline on-time performance distorted the incentives of airlines to manipulate arrival times. Yet, to my knowledge, I am the first to empirically show the side effects of quality disclosure in terms of perceived utility on the buyers' side. In particular, the results of my study show that disappointment effect may be present even when the certification leads to better sellers' performances.

My work also contributes to the empirical literature about reference-dependent preferences. In his review, Barberis (2012) points out that few papers document the relevance of reference-based preferences outside the areas of finance and choice under uncertainty. My paper shows the importance of reference points in a new setting related to the introduction of quality disclosures. In the literature of reference point formation, the work by Backus et al. (2017) is the closest to mine. They study reference points in an online setting and focus on a hybrid format of the online auctions in eBay in which each buyer has the "Buy-It-Now" (BIN) option to buy at any moment the product at a specific price without taking part in the auction. They find that eBay's buyers who presented the highest bid and lost the auction since another buyer used the BIN option, have significantly higher chances to leave the platform. They interpret this behavior through the lenses of reference-dependent preferences and argue that buyers' disappointment is the main driver for their exit choice.

Finally, I argue that my paper also contributes to the growing literature about the potential bias in online reviews. Several papers show that online reviews may be biased since reviewers may act strategically (Klein et al., 2016), or being influenced by previous reviews (Moe and Schweidel, 2009). Regarding movie reviews, the closest paper to mine is Lee et al. (2015). They show that the behavior of online reviewers is influenced by prior ratings, especially when reviewers' friends have rated a movie. They observe that friends' ratings induce reviewers' herding behavior. Accordingly, my paper presents additional evidence about the role of "external" factors influencing the reviewers' behavior. In contrast with the previous literature, I analyze the impact of expectations taking advantage of an exogenous change due to the AMPAS nominations.

2.3 Empirical Setting and Dataset

In this Section, first I present the movie recommendations platform, MovieLens, and I explain the timing and functioning of its rating process. Then, I describe the MovieLens 20M Dataset and how I enriched it with the information regarding nominations for the AMPAS Awards. Finally, I provide descriptive statistics concerning nominated and not nominated movies before and after nominations.

2.3.1 MovieLens

MovieLens (http://www.movielens.org) is an online platform run by the Department of Computer Science and Engineering at the University of Minnesota.

Figure 2.1: Snapshot of MovieLens.org: Main Page

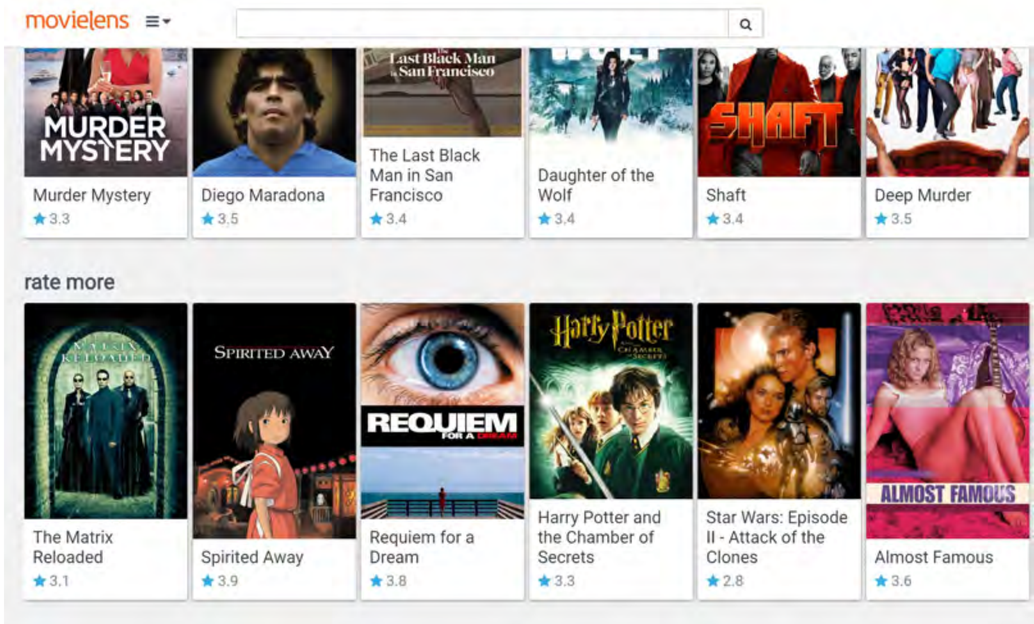
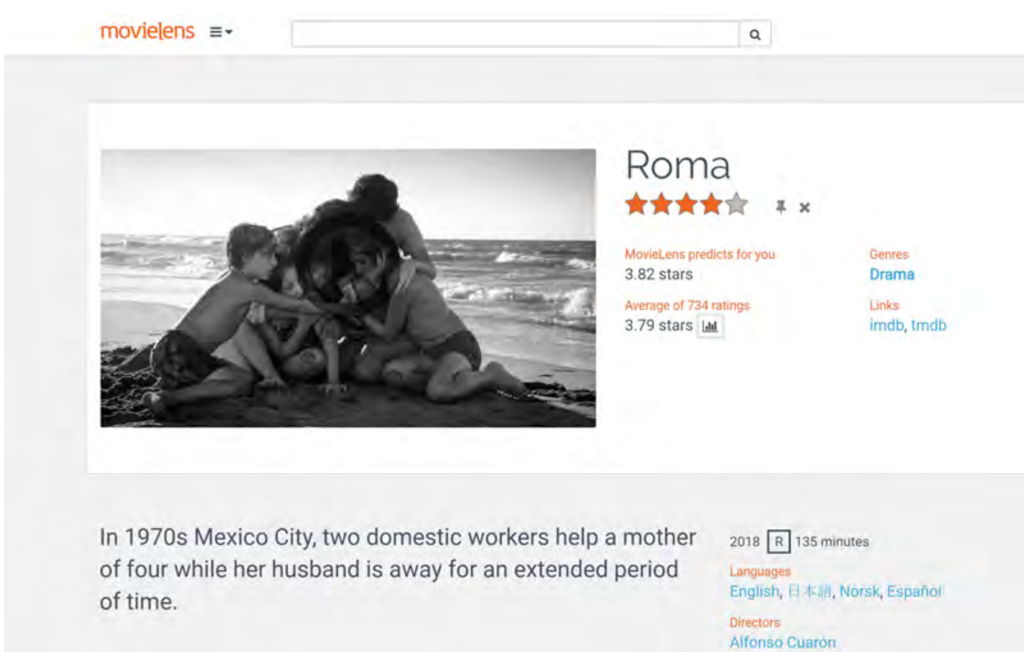


Figure 2.2: Snapshot of MovieLens.org: Movie Page



It provides movie recommendations for its users. Inscribed users are invited to rate movies. Then, following their preferences, the MovieLens algorithm creates a list of personalized recommended movies. MovieLens was launched in 1997 and from that time it has become a visible recommendation system. According to the work by Chen et al. (2010), in April 2006, over 13 million user ratings of 9,043 movies were present in MovieLens. Although the rating process experienced some minor changes in the design of the platform, the main mechanism remained unaltered.

Here I briefly describe the current rating process.[2] Figure 2.1 shows a snapshot of the MovieLens main page in which a group of movies is listed. If a user is interested in a movie, or a genre, she may type the desired query on the bar of top of the main page to get a more refined search. After clicking on a movie title, a user is redirected to the movie webpage (Figure 2.2) where she has access to further information such as the movie's synopsis, genre, year, the average rating by previous users who rated the movie, and the predicted rating assigned the user by the algorithm. Then, each user can rate a movie on a 0.5 to 5 star scale; and future recommendations are affected by the rating.

2.3.2 MovieLens 20M Dataset

The GroupLens group makes publicly available different types of datasets regarding MovieLens ratings. I use the "MovieLens 20M" Dataset generated in October 2016. It contains 20,000,263 ratings for 27,278 movies by 138,493 users displayed between January 1995 and March 2015. Each rating is linked with the identification numbers of the movie and the user, and with the date in which the rating is displayed on the platform. Not the entire universe of ratings from 1995 to 2005 is present in the dataset. Users were randomly selected with all users having rated at least twenty movies. No information is available for users apart from their identification number. Conversely, some movie characteristics (such as the movie genre, or release year) are directly available. Moreover, I complement the information in the dataset scraping further movies' characteristics with the corresponding link to the IMDb webpage (http://www.imdb.com). With this additional data, I have detailed information about movies' director, main actors, and actresses in the cast; movie's language, country of production, and first release day.

2.3.3 AMPAS Academy Awards

From 1929, the Academy of Motion Picture Arts and Sciences (AMPAS) has assigned awards for excellence in cinematic achievements.

The awards are divided into several categories.[3] Still, some particularly relevant categories (the so-called "Big Five") usually receive the most of the public attention: Best Picture; Best Direction; Best Leading Actor and Actress; and Best Screenplay. Every year, the procedure for

[2] Harper and Konstan (2015) present a precise description of the changes in the recommendation algorithm and in the rating process occurred during the years on the platform.

[3] A number of categories has been discontinued. From 2001, the same group of twenty-four categories has been used for the awards.

the assignment of the awards consists of two steps. First, a restricted group of movies, usually composed of five movies, is nominated for each category among those movies that qualify for the award. To be nominated in a given year, a movie must open in the previous calendar year in the Los Angeles County. This rule differs for the "Best Foreign Language Film" award. Non-US movies are selected in each country and the nominated movies for this award are chosen among this pre-selected pool.[4]

Since 2004, the nominated movies have been announced in mid-January. Before 2004, the results were released at the beginning of February. Then, six weeks after the announcement, the AMPAS awards are presented with a ceremony in one of the main theaters in Hollywood. To evaluate the impact of the nominations to the AMPAS awards, I consider all the nominated and awarded movies from 1995 to 2015 focusing on the nominations for the "Big Five" awards, and the awards for the "Best Foreign Language Film", the "Best Documentary Feature", and the "Best Animated Feature Film". Accordingly, I select 544 nominated movies. Among them, 522 movies are matched with the MovieLens dataset.[5] Moreover, for each year, I use the day of the nomination to establish whether a rating for a nominated movie was displayed on the platform before or after the nomination.[6]

In order to do the same for movies that were not nominated, I associate each not nominated movie with a nomination date. To do that, I follow a similar criterion to the one used by the Academy to select movies that qualify for the awards.

I consider the date of the first rating appearing on MovieLens for each movie; then, I select the first nomination ceremony after this date as the reference year of nomination. Finally, I remove all movies if their first rating on the platform is displayed more than two years after their year of production. In this way, I abstract from the ratings for old movies that cannot be compared with the most recent ones.

2.3.4 Descriptive Statistics

I conclude this Section with some relevant descriptive statistics about nominated and not nominated movies present in the dataset. I divide my analysis in two parts.

First, I report movies' statistics regarding all ratings available. Then, I focus on the window of 120 days around the AMPAS nominations (60 days before and 60 days after) in accordance with the empirical designs I will use to capture the impact of the nominations over movie ratings.

Table 2.1 shows and compares some relevant statistics for nominated and not nominated movies using all ratings available for each movie. The first three rows compare the average ratings and show that nominated movies have higher ratings (0.62 stars), in line with the assumption that nominated movies have higher quality. The average ratings for not nominated movies seem to not vary before and after the nominations, whereas a decrease is observable

[4]The official AMPAS webpage (https://www.oscars.org/oscars/rules-eligibility) provides more information about the movies' selection process.

[5]The unmatched nominated movies are documentaries (17) and foreign movies (5).

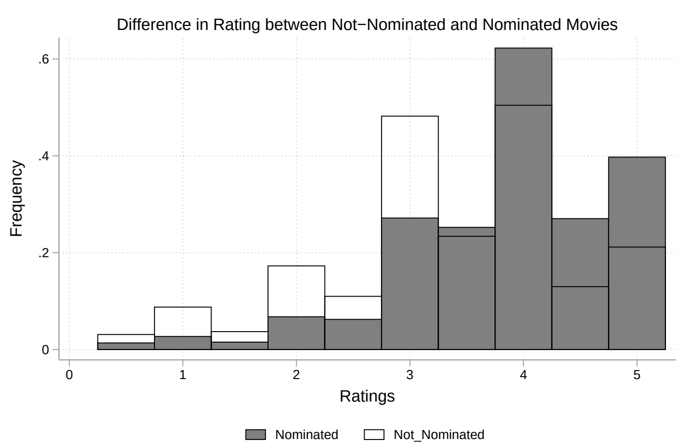
[6]The information about the nomination dates is extracted from the official AMPAS webpage and the associated Wikipedia entries.

for nominated movies. Nominated movies are also rated more frequently before and after nominations; they are rated for a longer period (Row 7) and they start to be rated before not nominated movies (Row 8). To visualize the difference in ratings between movies, Figure 2.3 shows the distributions of ratings for nominated and not nominated movies considering only ratings displayed before nominations. In line with the previous results, nominated movies have higher ratings.

Nominated and not nominated movies have also different genres (Rows 9 - 13) and they select different pool of users. Rows 14 and 15 show the average ratings reported by MovieLens users who rate not nominated and nominated movies before and after nominations. Nominated movies seem to attract users with higher average ratings relative to not nominated movies. That can be explained by users differing in the probability to report a high rating; or by the fact that users are attracted by different movies. Certain users may only watch high-quality movies and thus they report high ratings.

The statistics reported in Table 2.2 focus on the window of 120 days around the AMPAS nominations. The first panel (Rows 1-7) shows the evolution of the average ratings for not nominated and nominated movies before and after the nominations. Not nominated movies present stable ratings around the nomination day. Conversely, the ratings of nominated movies slightly drop (0.05 stars) around 10 days after the nominations. The second panel (Rows 8-14) shows the evolution of the number of ratings displayed before and after the nominations. Nominated movies are rated almost five times more than not nominated movies. Still, the dynamics of the number of ratings is quite stable for both groups.[7]

Figure 2.3: Difference in Ratings between Not Nominated and Nominated Movies



Note: The figure shows the distributions of ratings for not nominated and nominated movies considering only pre-nomination ratings. Nominated movies (in gray) have higher ratings than not nominated movies.

[7]Figures B.1 and B.2 show the dynamics of the arrival of movie ratings. The great majority of ratings occurs after nominations since movies are often released a few months before the AMPAS nominations and awards.

Table 2.1: Summary Statistics: Not Nominated and Nominated Movies

	Not Nom. (1)	SD	Nom. (2)	SD	Δ	$p-value$
Average Ratings						
Total	3.12	0.58	3.73	0.23	-0.62	0.00
Before Nominations	3.11	0.69	3.84	0.34	-0.74	0.00
After Nominations	3.13	0.59	3.73	0.23	-0.60	0.00
Number of Ratings						
Total	955.29	3,246.14	5,048.08	8,493.16	-4,092.78	0.00
Before Nominations	172.47	873.88	360.00	622.40	-187.53	0.00
After Nominations	782.82	2,655.42	5,448.19	8,175.50	-4,665.37	0.00
Rating Period (date - date)						
Last rating - First rating	2,521.06	2,197.51	3,297.15	2,043.76	-776.10	0.00
First rating - Release	263.22	273.67	152.68	165.30	110.54	0.00
Genres (%)						
Action	14.01	-	6.51	-	-	-
Adventure	4.08	-	8.28	-	-	-
Comedy	26.15	-	15.38	-	-	-
Drama	27.66	-	42.21	-	-	-
Others	28.1	-	27.62	-	-	-
Average Ratings for Users						
Before Nominations	3.47	0.42	3.49	0.42	-0.02	0.00
After Nominations	3.44	0.46	3.53	0.44	-0.09	0.00
Number of Ratings by Users						
Before Nominations	248.81	403.06	368.16	436.65	-119.35	0.00
After Nominations	321.67	365.30	248.36	298.04	73.31	0.00
Number of movies	10,817	-	507	-	-	-
Number of ratings	9,256,797		2,524,039	-	-	-

Note: In the first four sections, the table compares not nominated and nominated movies in terms of average ratings, number of ratings, rating periods, and genres. In the last two sections, the table compares the characteristics of users who rate nominated and not nominated movies before and after the nomination. In particular, I study the average rating reported by users and the total number of ratings present on the platform for each user. All ratings are considered for all not nominated and nominated movies if their first rating is displayed on the platform in the first two years after the year of production.

Table 2.2: Not Nominated and Nominated Movies 120 Days around the AMPAS Nominations

	Not Nom.	SD	Nom.	SD	Δ	$p-value$
Average Ratings						
from -60 to -30 days	3.17	0.78	3.85	0.42	-0.67	0.00
from -30 to -20 days	3.18	0.81	3.84	0.43	-0.66	0.00
from -20 to -10 days	3.17	0.80	3.84	0.49	-0.67	0.00
from -10 to 0 days	3.18	0.82	3.83	0.48	-0.65	0.00
from 0 to 10 days	3.19	0.81	3.84	0.49	-0.65	0.00
from 10 to 20 days	3.18	0.79	3.80	0.45	-0.62	0.00
from 20 to 30 days	3.18	0.82	3.82	0.49	-0.63	0.00
from 30 to 60 days	3.21	0.78	3.81	0.44	-0.60	0.00
Number of Ratings						
from -60 to -30 days	9.82	33.33	39.84	72.56	-30.02	0.00
from -30 to -20 days	5.22	16.18	25.40	41.03	-20.18	0.00
from -20 to -10 days	5.91	19.64	26.26	40.34	-20.35	0.00
from -10 to 0 days	4.98	14.78	26.43	37.30	-21.44	0.00
from 0 to 10 days	4.25	12.31	24.93	33.23	-20.68	0.00
from 10 to 20 days	4.40	13.44	26.54	34.60	-22.15	0.00
from 20 to 30 days	4.79	16.58	26.94	35.64	-22.15	0.00
from 30 to 60 days	9.17	32.98	54.46	67.75	-45.29	0.00
Number of movies	10,817	-	507	-	-	-
Number of ratings	241,513		204,144	-	-	-

Note: The table compares not nominated and nominated movies in terms of average ratings and number of ratings in the window of 120 days around the AMPAS nominations . All ratings are considered for all not nominated and nominated movies if their first rating is displayed on the platform in the first two years after the year of production.

2.4 Theoretical Framework

In this Section, I present a conceptual framework to model the effect of the AMPAS nominations on the reviewing behavior by users. This theory is developed to clarify the two main channels through which a shift in expectations may affect movie ratings: disappointment/elation and selection. Accordingly, first I proceed with a formal description of the user's decision to watch and rate a movie (the rating process) keeping fixed users' expectations. Then, I study the impact of a change in expectations due to a shock such as the AMPAS nominations, and I present the empirical predictions derived from this framework.

2.4.1 The Rating Process

Each movie is defined by $M+1$ parameters: a quality parameter $\theta_i \in \mathbb{R}$, and a vector $\boldsymbol{\mu_i} \in \mathbb{R}^M$ describing the movie "position" in the feature space with M dimensions (for instance: the movie's genres). Similarly, each user is defined by $M+1$ parameters: $v_j \in \mathbb{R}$ regarding the utility that user j receives by going to the theater (irrespectively of the movie watched), and a vector $\boldsymbol{\pi_j} \in \mathbb{R}^M$ describing the "position" of user j preferences in the feature space.

Before watching movie i, users do not observe the quality of a movie. Thus, the expected utility for user j watching movie i is defined as follows:

$$E(u_{ij}) = E(\theta_i) + v_j - d(\boldsymbol{\pi_j}, \boldsymbol{\mu_i}), \tag{2.4.1}$$

where the function $d(.)$ is a strictly increasing, continuous norm describing the distance between the position of movie i and the preferences of user j. Here I consider the Euclidean distance:[8]

$$d(\boldsymbol{\pi_j}, \boldsymbol{\mu_i}) = \sqrt{\sum_{m=1}^{M} (\pi_{jm} - \mu_{im})^2}.$$

Accordingly, it is possible to rewrite the expected utility as $E(u_{ij}) = E(\theta_i) + \alpha_{ij}$ with $\alpha_{ij} = v_j - d(\boldsymbol{\pi_j}, \boldsymbol{\mu_i})$ representing the sum of the parameters related to the utility derived by going to the theater and the "match" value in terms of utility between user j and movie i.

After watching movie i, the quality is observed by user j. In line with Koszegi and Rabin (2006), the expected utility $E(u_{ij})$ defines the reference point for user j about movie i. Thus, the ex-post utility for user j after watching movie i is the following:

$$\begin{aligned} u_{ij} &= \theta_i + \alpha_{ij} + \gamma(\theta_i + \alpha_{ij} - E(u_{ij})) \\ &= \theta_i + \alpha_{ij} + \gamma(\theta_i - E(\theta_i)), \end{aligned} \tag{2.4.2}$$

where $\gamma(.)$ represents the user's gain-loss utility factor as in Koszegi and Rabin (2006). In the reference point formation literature, γ is a function of the gain/loss term $\theta_i - E(\theta_i)$ (Kahneman and Tversky, 1979; Loomes and Sugden (1982); Koszegi and Rabin, 2006; Backus et al., 2017). For simplicity, I assume $\gamma(.)$ to be constant. With $\gamma > 0$, it is possible to capture the disappointment effect in users' utility: the higher the expectations of user j regarding the quality of movie i, $E(\theta_i)$, the lower the user j gain-loss utility term.

For each movie i, the following timing describes the process through which users are informed about the movie, they decide to watch it and, in such a case, rate it:

1. Movie i is released and a unit measure of potential users associated with movie i is formed. Users are heterogeneous in α_{ij} and the distribution of α_{ij} among all potential users is $F(\alpha)$;

2. A signal s appears and a proportion $\lambda(s) \in (0,1)$ becomes aware of movie i. The distribution of α_{ij} among aware users after signal s is $F_s(\alpha)$;

3. Aware users form expectations about the quality of the movie $E(\theta_i|s)$ and watch movie i if $E(u_{ij}|s) = E(\theta_i|s) + \alpha_{ij} > 0$;

[8] All theoretical results can be extended to other strictly increasing, continuous norm distances.

4. Finally, users who watch the movie always rate it reporting their ex-post utility. Accordingly, the rating of user j for movie i, r_{ij}, is equivalent to the ex-post utility: $r_{ij} = u_{ij}$.[9]

2.4.2 The Impact of Signals

Signals change the profile of users who are aware of movies ($F_s(\alpha)$ depends on s) and they affect the quality that all aware users expect by movies. Accordingly, we may interpret signal s as the result of an advertising campaign promoted by the movie producer, or of a quality disclosure such as the AMPAS nominations: they jointly impact the expectations about a movie and the potential audience becoming aware of the movie release.

These two effects influence the profile of users who decide to watch the movie and, as a final result, the observed ratings. Specifically, the expected ratings of movie i given quality θ_i and signal s is the following:

$$E(r_{ij}|\theta_i, s) = \theta_i + \int_{\alpha > -E(\theta_i|s)} \alpha dF_s(\alpha) + \gamma(\theta_i - E(\theta_i|s)). \tag{2.4.3}$$

To have a better sense of the impact on ratings from a shift in the expected movie quality, I assume signals to change from s to s^+ such that $E(\theta_i|s) < E(\theta_i|s^+)$. The difference in expected ratings is the following:

$$\begin{aligned} E(r_{ij}|\theta_i, s^+) - E(r_{ij}|\theta_i, s) = &- \gamma(E(\theta_i|s^+) - E(\theta_i|s)) \\ &+ \int_{\alpha > -E(\theta_i|s^+)} \alpha dF_{s^+}(\alpha) - \int_{\alpha > -E(\theta_i|s)} \alpha dF_s(\alpha). \end{aligned}$$

I define the first term ($-\gamma(E(\theta_i|s^+) - E(\theta_i|s))$) as the *disappointment effect* since, when $\gamma > 0$, it reflects the downward effect on ratings of an increase in the expectations. Conversely, the second term ($\int_{\alpha > -E(\theta_i|s^+)} \alpha dF_{s^+}(\alpha) - \int_{\alpha > -E(\theta_i|s)} \alpha dF_s(\alpha)$) represents the *selection effect* on the profile of users who decide to watch movie i resulting from the shift in signal. While the disappointment effect has always a downward effect on ratings (with $\gamma > 0$), the effect of selection is ambiguous. With $F_s(\alpha) = F_{s^+}(\alpha)$, selection drives ratings downward, but, if $F_s(\alpha) \neq F_{s^+}(\alpha)$, an upward effect on ratings is possible.[10] I illustrate this point with the following example.

Example 1. *Assume that $E(\theta_i|s) = -1$ and $E(\theta_i|s^+) = 0$. With $F_s(\alpha) = F_{s^+}(\alpha) = \Phi(0, 1)$, the disappointment effect equals to $-\gamma < 0$, and the selection effect equals to $(0.798 - 1.525) < 0$. Therefore, both disappointment and selection effects depress ratings after a change in signal. This may not be the case when the change in signals affects the distribution of α_{ij} among users*

[9] This may not be an innocuous assumption since users' rating decision may depend on their ex-post utility levels. In particular, Dellarocas and Wood (2006) and Nosko and Tadelis (2015) claim that online users who rate products are more likely to be the ones who experienced more "extremely" positive or negative utility levels from the transactions. In line with this perspective, I discuss in the next Subsection how a change in expectations may affect ratings throughout the selection channel.

[10] Assuming $F_s(\alpha) \neq F_{s^+}(\alpha)$ is in line with the summary statistics reported in Table 1.1, showing different average ratings by users who rate nominated movies before and after nominations.

who are aware of the movie. For instance, before receiving a nomination (with signal s), the distribution of users who are aware of movie i may be quite concentrated around the mean: $F_s(\alpha) = \Phi(0,1)$. Conversely, after the nomination (with signal s^+), the aware users have more dispersed levels of α_{ij} and $F_{s^+}(\alpha) = \Phi(0,4)$. In this case, users' selection effect equals to $(1.595 - 1.525) > 0$ and it has an upward impact on ratings.

The following observation recaps the results from the previous discussion.

Observation 1. *Assume the signal about movie's quality changes from s to s^+ such that $E(\theta_i|s) < E(\theta_i|s^+)$. The difference in movie ratings with different signals $E(r_{ij}|\theta_i, s^+) - E(r_{ij}|\theta_i, s)$ is composed by disappointment and selection. With $\gamma > 0$, disappointment moves downward users' ratings, whereas the effect of selection is ambiguous.*

2.4.3 Isolating the Disappointment Effect

According with Observation 1, the comparison of ratings reported by users with different signals cannot isolate the effect of disappointment from selection. Yet, this may be possible once we compare ratings posted by the same user for different movies. In particular, I denote the difference in ratings posted by user j about movie i and h as $\Delta^j_{ih} = r_{ij} - r_{hj}$. Recalling the previous definition of ratings as the ex-post users' utility, Δ^j_{ih} includes three different terms:

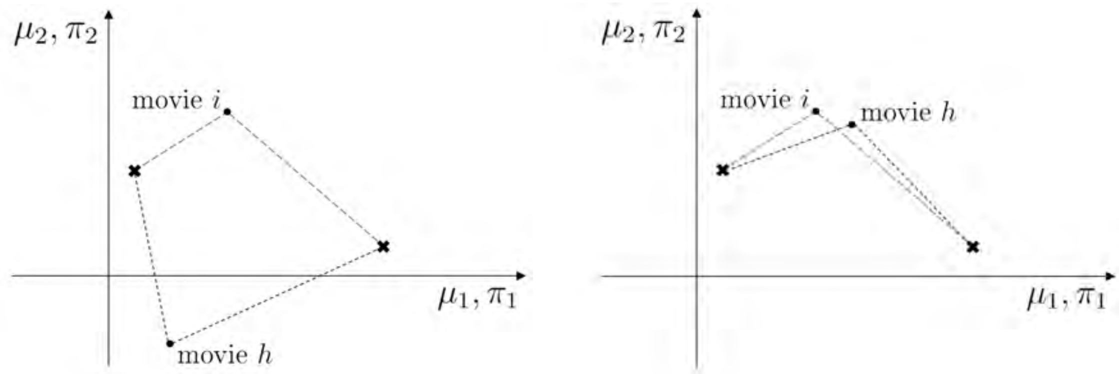
$$\begin{aligned}\Delta^j_{ih} &= (\theta_i - \theta_h) - (\alpha_{ij} - \alpha_{ih}) + \gamma(\theta_i - E(\theta_i|s_{ij}) - \theta_h + E(\theta_h|s_{hj}))\\ &= (\theta_i - \theta_h)(1+\gamma) - (\alpha_{ij} - \alpha_{ih}) - \gamma(E(\theta_i|s_{ij}) - E(\theta_h|s_{hj}))\\ &= (\theta_i - \theta_h)(1+\gamma) - (d(\boldsymbol{\pi_j}, \boldsymbol{\mu_i}) - d(\boldsymbol{\pi_j}, \boldsymbol{\mu_h})) - \gamma(E(\theta_i|s_{ij}) - E(\theta_h|s_{hj})),\end{aligned} \tag{2.4.4}$$

where s_{ij} and s_{hj} are the signals received by user j before watching and rating movie i and movie j, respectively. The first term, $(\theta_i - \theta_h)(1+\gamma)$, is proportional to the difference in quality of the two movies and does not vary with signals; the second term, $(d(\boldsymbol{\pi_j}, \boldsymbol{\mu_i}) - d(\boldsymbol{\pi_j}, \boldsymbol{\mu_h}))$, regards the distances in terms of features of two movies relative to the preferences of user j; finally, the last term, $\gamma(E(\theta_i|s_{ij}) - E(\theta_h|s_{hj}))$ describes the difference in terms of expectations by user j regarding the movies' qualities.

Studying the difference between ratings posted by the same user removes only a part of users' components of ratings (the utility parameter v_j). In particular, the match values between user j and the two movies do not disappear.

Still, when movie i and movie h share a "similar" position in the feature space, users' components of ratings reduce as shown in Figure 2.4. Here, the two graphs show a two-dimensional feature space (for instance the main and the secondary genre) in which the points denoted with a cross ($\times$) represent the preferences of two different users; whereas the points denoted with a dot ($\cdot$) represent the features of two different movies. When the movie's features are not similar (like in the figure on the left), the difference $d(\boldsymbol{\pi_j}, \boldsymbol{\mu_i}) - d(\boldsymbol{\pi_j}, \boldsymbol{\mu_h})$ is large since the distances between movie h and the users are not a good predictor for their distances from movie i. Conversely, if the movie's features are similar (like in the figure on the right), $d(\boldsymbol{\pi_j}, \boldsymbol{\mu_i}) - d(\boldsymbol{\pi_j}, \boldsymbol{\mu_h})$ is small and the distances between movie h and the users predict well their distances from movie i. More precisely, when movie i and movie h share the same features $\boldsymbol{\mu_i} = \boldsymbol{\mu_h} = \bar{\boldsymbol{\mu}}_{\boldsymbol{ih}}$, users' components of ratings totally vanish from the difference Δ^j_{ih}.

Figure 2.4: Variations in User Selection Comparing Different Movies



Therefore, once we restrict the attention to movies sharing the same features, we can isolate the disappointment effect due to a shift in the expectations of movie quality. To do that, it is necessary to study a situation in which only one movie receives a shock in its signal. Therefore, we can study the expected Δ^j_{ih} when the signal for movie i changes from s_i to s_i^+, whereas the signal for movie h remains constant to s_h:

$$E(\Delta^j_{ih}|\theta_i, \theta_h, s_i^+, s_h) - E(\Delta^j_{ih}|\theta_i, \theta_h, s_i, s_h) = -\gamma(E(\theta_i|s_i^+) - E(\theta_i|s_i)). \tag{2.4.5}$$

To recap this result, I present the following observation.

Observation 2. *Consider two movies i and h sharing the same position in the feature space such that $\boldsymbol{\mu_i} = \boldsymbol{\mu_h} = \boldsymbol{\bar{\mu}_{ih}}$. Assume the signal about quality for movie i changes from s_i to s_i^+ such that $E(\theta_i|s) < E(\theta_i|s^+)$; and the the signal about quality for movie h remains constant to s_h. The difference in Δ^j_{ih} with different signals $E(\Delta^j_{ih}|\theta_i, \theta_h, s_i^+, s_h) - E(\Delta^j_{ih}|\theta_i, \theta_h, s_i, s_h)$ is only composed by the disappointment effect.*

In the following Section, I present two empirical designs to identify disappointment due to a change in users' expectations. Following the same approach used in the theoretical framework, I start studying the variations in ratings before and after the nomination for nominated movies.

I show supporting evidence to document the change in moviegoers' characteristics before and after the nomination. To account for the selection effect, I use not nominated movies as control group. Doing so, I assume not nominated movies to not be treated by the nomination shock; and I support this assumption by looking at their rating variations after nomination. This is in line with the theoretical result highlighted in Observation 2 where the signal of the not nominated movie h remains constant to s_h.

First, I develop a DiD strategy that cannot fully disentangle disappointment from selection. Then, I present a cluster analysis technique that allows to match similar movies in order to replicate the condition $\boldsymbol{\mu_i} = \boldsymbol{\mu_h} = \boldsymbol{\bar{\mu}_{ih}}$. Finally, I present a new design embedding pre-treatment matching and difference-in-difference to isolate the disappointment effect as it is reported in Equation 2.4.5.

2.5 Identification Strategy

In this Section, I propose two empirical strategies. In both designs, I assume that movies nominated for the AMPAS awards receive an upward shift in users' expectations about their quality. With the first strategy, I measure changes in ratings for nominated movies after the nomination controlling for the variation of ratings occurring to not nominated movies. In this way, following Observation 1, it is not possible to disentangle disappointment from selection, apart from controlling for the observable characteristics of users. Conversely, in the second strategy, I study variations in the differences of ratings reported by the same user for movies with similar features. Doing that, I remove the bias due to the selection effect in line with Observation 2.

Users' expectations may be affected by a variety of marketing activities. Thus, in both strategies, I focus on a limited window of days around the AMPAS nominations.[11] In this way, I try to isolate the impact of AMPAS nomination events on users' expectations. As a direct consequence of this focus, I can only identify the short-run effect of an increase in expectations.

2.5.1 Difference-in-Difference

In this empirical design, I use movie ratings as a response variable. With a Difference-in-Difference (DiD) strategy, I study the variation in ratings before and after the AMPAS nomination dates for nominated movies, controlling for the variation occurred to not nominated movies. Accordingly, the control group (not nominated movies) provides the counterfactual dynamics of ratings for nominated movies in case they did not receive a nomination. The main equation is:

$$r_{ij} = \alpha + \theta_i + v_j + \beta_1 Nom_i + \beta_2 T_{ij} + \beta_3 Nom_i \times T_{ij} + \boldsymbol{\delta X_{ij}} + \epsilon_{ij}, \tag{2.5.1}$$

where r_{ij} is the rating for movie i by user j. θ_i and v_j are movie i and user j fixed effects, respectively. Nom_i takes value 1 if movie i is nominated, and 0 otherwise; T_{ij} takes value 1 if rating r_{ij} is displayed after the nomination date associated with movie i, and 0 otherwise. $\boldsymbol{X_{ij}}$ is a set of control variables regarding movie's and user's characteristics. I divide this set into two groups: 1) time-invariant movie variables that are identified only when I do not use movie fixed effect: $US - Release_i$, $US - Production_i$ and $English - Language_i$ are three dummy variables taking value 1 if movie i is first released in US; if movie i is produced in US; or, if movie i's main language is English, respectively. $Director - Nominated_i$, $Director - Awarded_i$, $Stars - Nominated_i$, and $Stars - Awarded_i$ are four dummy variables taking value 1 if movie i's director has ever been nominated for AMPAS awards, or has ever won the AMPAS awards; and, if movie i's three main stars have ever been nominated for AMPAS awards, or have ever won the AMPAS awards, respectively.[12] 2) time-variant variables: $diff_{ij}$, the distance between the day of rating r_{ij} and the nomination day of movie i; $\bar{r}_{jt-1}$, the average rating by user j before

[11] In the main text I always consider a window of 30 days before and after the nomination; in Appendix 2.10, I repeat the main analysis considering a 60-day window before and after the nomination.

[12] The identities of the director and of the three main stars of movies are provided by the scraped data from IMDb.

rating movie i; n_{jt-1}, the number of posted ratings by user j before rating movie i. Controlling for these variables may be relevant to capture variations in users' features, and thus to isolate the disappointment component from selection.

Using not nominated movies to determine the counterfactual dynamics for nominated movies after nomination may be disputable. Not nominated movies and nominated movies differ in ratings before nomination (see Tables 1.1 and 2.2 and Figure 2.3). Accordingly, using movie fixed effects or controlling for movie characteristics (in $\boldsymbol{X_{ij}}$) is key in order to compare relatively similar movies and replicate the condition of a proper "random assignment" of the shock (in this case the AMPAS nominations).

Yet, looking at ratings before nominations, the dynamics of the treated (nominated) and the control (not nominated) groups are similar. To document these trends, I perform two event-studies separately for nominated and not nominated movies. I regress ratings r_{ij} over a full set of dummy variables for each group of five days around nominations from 60 days before to 30 days after:

$$r_{ij} = \alpha + \sum_{t=-60}^{30} \delta_\tau \mathbb{1}(\tau = t) + \epsilon_{ij}. \tag{2.5.2}$$

Figures 2.5 and 2.6 show the estimated coefficients δ_τ for nominated and not nominated movies, respectively. The coefficients show a parallel, slightly negative trend before nominations for both groups (confirming the evidence of Table 2.2).

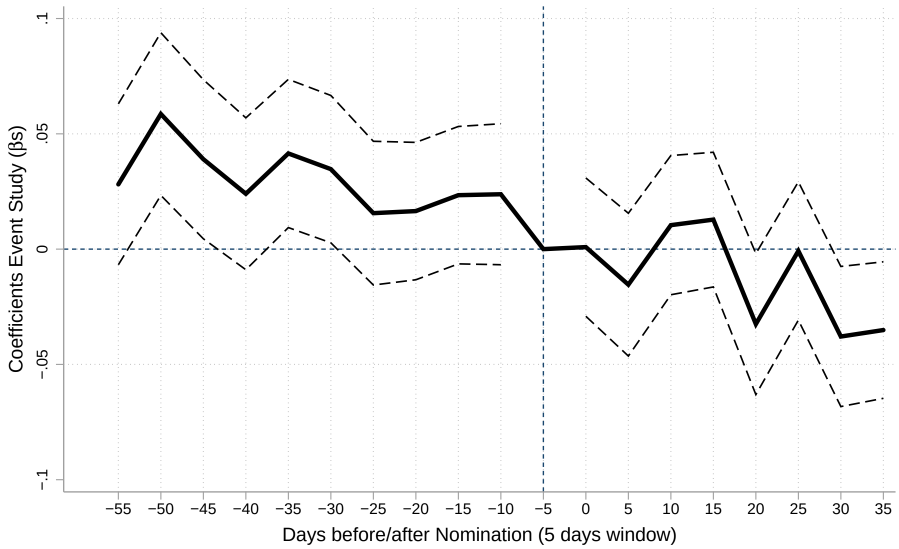
Moreover, not nominated movies do not seem to receive a positive shift in their ratings after nomination (at least not of the same magnitude relative to nominated movies). This is in line with the previous assumption according to which not nominated movies are not treated at all. If this was not the case, the parameter β_3 would capture users' disappointment for nominated movies, together with users' surprise or elation for not nominated movies. Using the notation from the previous theoretical framework, this could be equivalent to compare the dynamics of ratings for a movie i that receives a change in signal from s_i to s_i^+ with $E(\theta_i|s_i) < E(\theta_i|s_i^+)$ (the movie is nominated), with a movie h receiving a change in signal from s_h to s_h^- with $E(\theta_h|s_h) > E(\theta_h|s_h^-)$ (the movie is not nominated). Not being nominated does not seem to positively affect ratings after nomination, and we may conclude that the impact on expectations of signal s_h^- is relativel small: $E(\theta_h|s_h) \sim E(\theta_h|s_h^-)$.[13]

I conclude this analysis with a third event study design to check the parallel trends between treated and control groups. Extending the identification presented in Equation 2.5.1, I substitute the indicator T_{ij} with multiple dummy variables for each group of five days around nominations:

$$r_{ij} = \alpha + \beta_1 Nom_i + \sum_{t=-60}^{30} \delta_\tau \mathbb{1}(\tau = t) + \sum_{t=-60}^{30} \beta_\tau Nom_i \times \mathbb{1}(\tau = t) + \epsilon_{ij}. \tag{2.5.3}$$

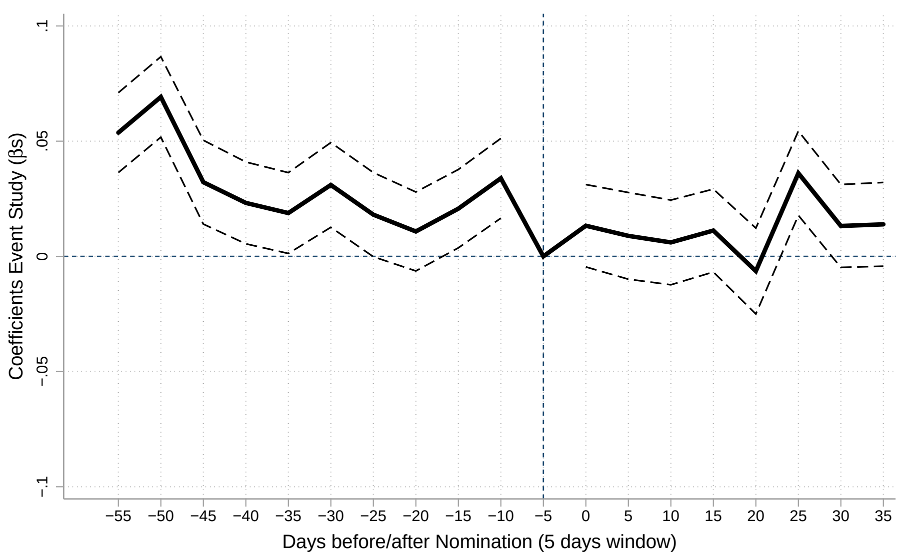
[13]Yet, even with $E(\theta_h|s_h) > E(\theta_h|s_h^-)$, the parameter β_3 can still be interpreted as the empirical estimate of the disappointment/elation coefficient γ.

Figure 2.5: The Event Study Graphs around the AMPAS Nominations for Nominated Movies



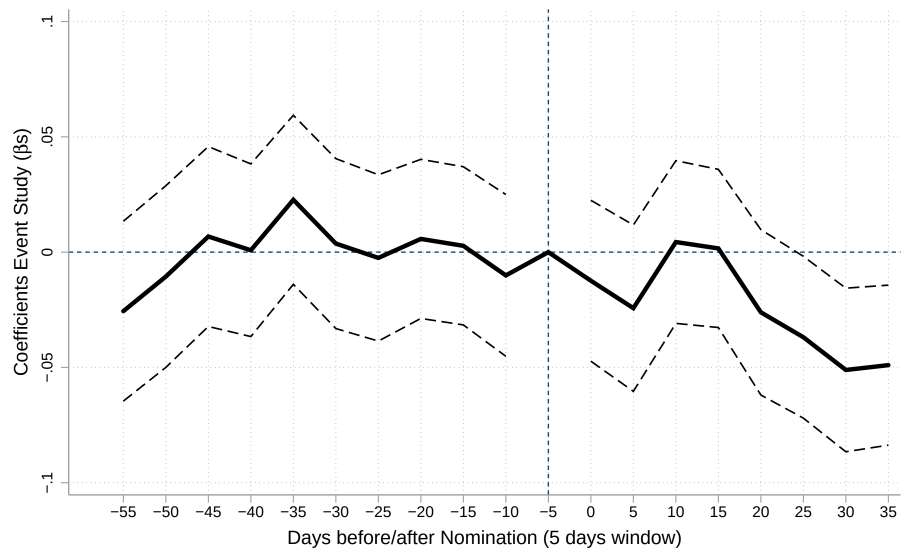
Note: The figure shows the dynamics of the parameters δ_τ of Equation 2.5.2 around the AMPAS Nominations starting 60 days before until 30 days after for Nominated Movies. 95% confidence intervals with s.e. clustered at movie and 5-day window level are displayed.

Figure 2.6: The Event Study Graphs around the AMPAS Nominations for Not Nominated Movies



Note: The figure shows the dynamics of the parameters δ_τ of Equation 2.5.2 around the AMPAS Nominations starting 60 days before until 30 days after for Not Nominated Movies. 95% confidence intervals with s.e. clustered at movie and 5-day window level are displayed.

Figure 2.7: The Event Study Graph around the AMPAS Nominations



Note: The figure shows the dynamics of the parameters β_τ of Equation 2.5.3 around the AMPAS Nominations starting 60 days before until 30 days after. 95% confidence intervals with s.e. clustered at movie and 5-day window level are displayed.

Figure 2.7 reports the coefficients β_τ associated with the combinations between the variable Nom_i and the time dummy variables in Equation 2.5.3. No trend in the period before the nomination can be detected. This suggests again that nominated and not nominated movies follow comparable paths at least before the shock. In Appendix 2.9, I present two additional event-study graphs to show evidence in favor of the parallel-trend assumption. Figure B.3 shows the coefficients β_τ once I add all controls and fixed effects to Equation 2.5.3. In Figure B.4, I repeat the same analysis of Figure 2.7 for a longer span of days after the nomination.

Finally, I provide additional evidence in favor of the parallel trend assumption supporting the DiD design using a placebo test. In particular, I study the same specification expressed by Equation 2.5.1 shifting back the window of time by 30 days. In this way, I compare the dynamics of nominated and not nominated movies starting 60 days before the nomination and imposing a placebo shock 30 days before the actual day of AMPAS nominations.

To do that, I introduce a new indicator variable T_{ij}^{-30} taking value 1 if rating r_{ij} is displayed in the 30 days before the nomination date associated with movie i, and 0 otherwise (if r_{ij} is displayed between 60 and 30 days before the nomination). Table B.1 shows the results of the placebo test. I use different control and fixed effects, and, in all specifications, the parameter for $Nom_i \times T_{ij}^{-30}$ is always not significant and much smaller.

In Section 2.6, I extend the DiD analysis by separately studying movies that receive one or more AMPAS nominations; and movies that receive the AMPAS awards.

2.5.2 Difference-in-Difference with Movie Matching

The DiD design provides a credible way to measure the change in ratings for nominated movies after the AMPAS nominations. Still, it does not entirely exploit the dataset potential. In particular, the previous strategy does not take into account the available information regarding the movie/user matches before and after nominations. With the second design, I consider these features of the dataset to account for the selection effect.

To do that, I complement the DiD design by matching movies with similar features: therefore, I measure the variations of ratings for nominated movies, controlling for the changes that occurred to a subsample of not nominated movies.

A Different Response Variable

The response variable for the second design is the difference in ratings reported by the same user. In particular, for each nominated movie i, I construct the difference in ratings between i and each not nominated movie h rated by user j: $\Delta^j_{ih} = r_{ij} - r_{hj}$.[14]

Studying the dynamics of Δ^j_{ih} around the nomination dates for movie i is similar to apply user fixed effects (v_j) to the previous DiD strategy. Still, here I complement the user fixed effects by matching nominated movies with not nominated movies (rated by the same users) sharing similar features. Doing so, I can identify the disappointment effect and remove a further source of user selection in line with the theory presented in Subsection 2.5.2.

To this extend, I perform a cluster analysis using two unsupervised learning algorithms described in the next Subsection.[15] These algorithms aim at finding patterns in datasets and select categories. Accordingly, with a non-parametric matching among movies, I try to select nominated and not nominated movies sharing similar characteristics. Thus, restricting on couples of movies in the same cluster is equivalent to removing (or at least reducing) the selection effect due to the changes in users' preferences.

Cluster Analysis: k-mean and k-median Algorithms

Cluster analysis is an exploratory data-analysis technique used to find patterns and select categories for multidimensional datasets. In the last decades, several algorithms and methods have been proposed to group data. Here I use two different algorithms that have been successful in finding clusters in multiple contexts: k-mean and k-median algorithms.[16]

In this Subsection, I provide a short explanation of the functioning of these algorithms; then, I illustrate which variables I use to determine the clusters; and finally, I comment on the

[14] As before, only ratings displayed in a short window of days around the nomination are used. Moreover, only users who watch at least one nominated movie during the period of analysis are considered. In Table B.2, I compare some descriptive statistics between the users I select in this design relative to all users.

[15] MovieLens datasets have been often used as a laboratory to test recent techniques measuring similarity among movies. For a list of studies regardin cluster analyses performed on the MovieLens datasets see the webpage: https://grouplens.org/publications/.

[16] See Everitt et al. (2011) and Hastie et al. (2017) for a detailed exposition for unsupervised learning algorithms and other techniques to cluster data.

clustering results.

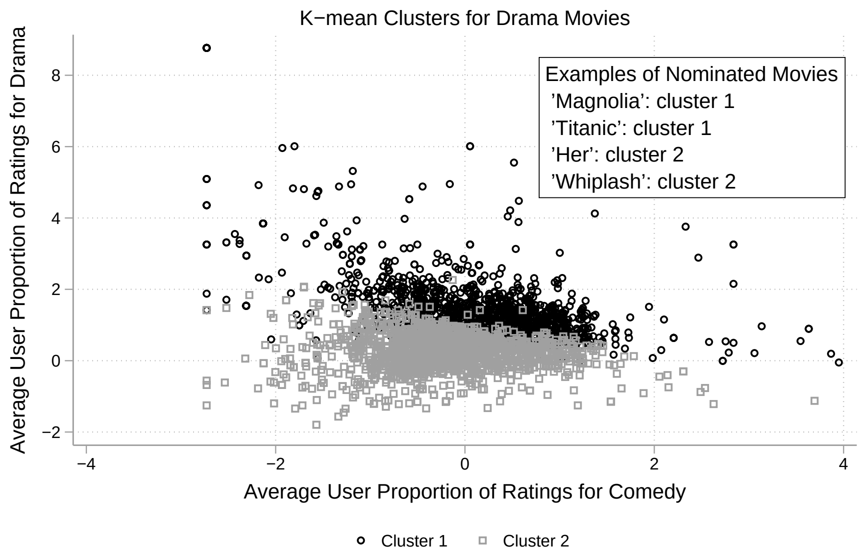
The k-mean and k-median algorithms are two unsupervised learning techniques to cluster data into different categories. Data are numeric and often multidimensional. Both algorithms assume the presence of a predetermined number of clusters, say k. Then, they randomly choose k points in the dimension space of the dataset; and they compute the (Euclidean) distance between each random point and all the observations composing the dataset. Each observation belongs to the cluster associated with the "closer" point k. In this way, the dataset is divided into k clusters and the average, or the median, observations over all the dimensions can be computed for each cluster.

Then, the process is repeated substituting the k random points with the k means, or the k medians, until the cluster centers (means and medians) converge. If there is not a good reason to choose a predetermined number of clusters (as it is in my case), the algorithm is repeated using different numbers of clusters k. The optimal k is chosen considering how distinct clusters are using the method proposed by Calinski and Harabasz (1974): a good clustering specification is the one in which the between-cluster variation is high and the within-cluster variation is low. Calinski and Harabasz (1974) proposed an index (analogous to an F-ratio) that is indicative of the performance of the clustering in terms of between- and within-cluster variations. In my analysis, I repeat nine times the k-mean and k-median algorithms for values of k that goes from 2 to 10.

I apply these clustering techniques to group movies in the following ways. First, I group movies for different genres and I perform the k-mean and the k-median clustering algorithms for each genre separately. I do this since genres appear to be an extremely relevant movie's feature and I want to separate movies with different features. Then, for each user j, I consider the proportion of movies rated by j (before nominations) belonging to a specific genre g over the total number of movies rated by j (before nominations). These ratios p_j^g are related to the preferences of user j in terms of genres. If user j only watches and rates "action" movies, then $p_j^{Action} = 1$, with all the other parameters equal to zero. After having computed p_j^g for each user and each genre, I derive for each movie i the average proportion of ratings $\bar{p}_i^g$ using all p_j^g of users who rated movie i.

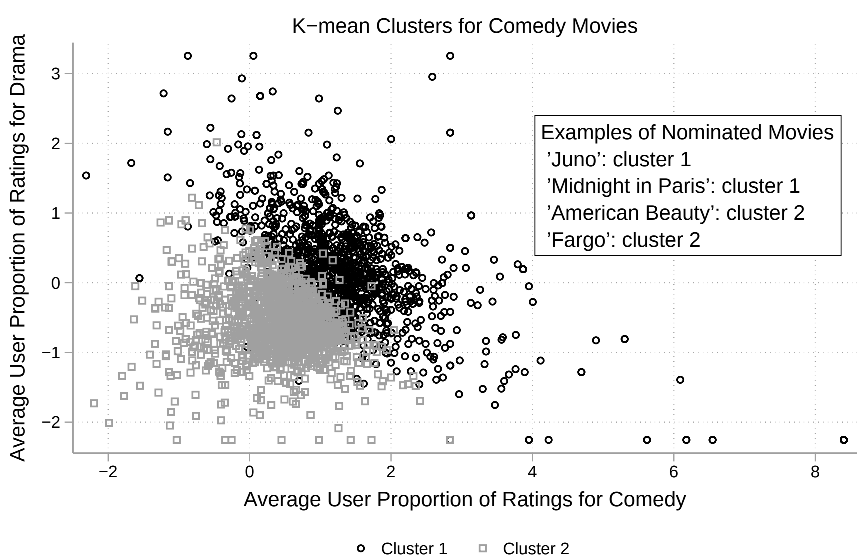
Accordingly, different values of $\bar{p}_i^g$ reveal which types of users rate movie i. I use k-mean and the k-median clustering to select different clusters of movies (that share the same genre) using the values of $\bar{p}_i^g$ for each movie. In this sense, a movie is characterized by twenty variables since the dataset divides movies into twenty genres. To have a sense of the clustering results, Figures 2.8 and 2.9 show scatter plots that display "drama" and "comedy" movies (the two more frequent genres) over the variables $\bar{p}_i^{Drama}$ and $\bar{p}_i^{Comedy}$. In both cases, the k-mean algorithm splits the dataset into two clusters with comparable results. Movies are grouped depending on the high or low values of $\bar{p}_i^{Drama}$ and $\bar{p}_i^{Comedy}$. In Appendix 2.9, Figure B.5 shows the same scatter plots for the eight most present genres. In the majority of the cases, two clusters are chosen.

Figure 2.8: K-mean Movie Clusters for Genre "Drama"



Note: The figure shows the scatter plot of "drama" movies over the variables $\bar{p}_i^{Drama}$ and $\bar{p}_i^{Comedy}$ (standardized). Each dot correspond to a movie and the movies are divided in two clusters following the k-mean algorithm.

Figure 2.9: K-mean Movie Clusters for Genre "Comedy"



Note: The figure shows the scatter plot of "comedy" movies over the variables $\bar{p}_i^{Drama}$ and $\bar{p}_i^{Comedy}$ (standardized). Each dot correspond to a movie and the movies are divided in two clusters following the k-mean algorithm.

Difference-in-Difference with Movie Matching: Regression

After having grouped movies in different clusters, it is possible to analyze the dynamics of Δ^j_{ih} around the AMPAS nomination dates in order to identify the disappointment effect.

In the following regression, once I restrict on movies h sharing the same genre and clusters with movie i, the coefficient β multiplying T_{ij} represents the impact of disappointment:

$$\Delta^j_{ih} = \alpha + \lambda_{ih} + \beta T_{ij} + \boldsymbol{\delta X^j_{ih}} + \epsilon^j_{ih}. \tag{2.5.4}$$

Here, λ_{ih} represents the movie i/movie h combination fixed effect; T_{ij} is, as before, an indicator variable taking value 1 if r_{ij}, the rating for the nominated movie i, is displayed after the nomination date, and 0 otherwise. Finally, $\boldsymbol{X^j_{ih}}$ is a set of the following control variables for movie i and h varying over time (all fixed characteristics are not identified by the presence of the movie-combination fixed effect) : $\bar{r}_{jt-1(h)}$ and $\bar{r}_{jt-1(i)}$ are the average ratings by user j before rating movie h and i, respectively; $\bar{r}_{ht-i(j)}$ and $\bar{r}_{it-i(j)}$ are the average ratings for movie h and i before the rating by user j, respectively. $n_{jt-1(h)}$ and $n_{jt-1(i)}$ are the number of ratings by user j before rating movie h and i, respectively.

This new identification design exploits the potential fixed effects enabled by the dataset; still, it continues to rely on the relationship between nominated and (a subsample of) not nominated movies to identify the parameter of interest. For this reason, it is relevant to provide evidence about the absence of pre-trends in the dynamics of Δ^j_{ih} before nominations. In particular, it is possible to extend the identification presented in Equation 2.5.4 with multiple dummy variables for each group of five days around the nominations as it is proposed for the DiD design (see Subsection 2.5.1):

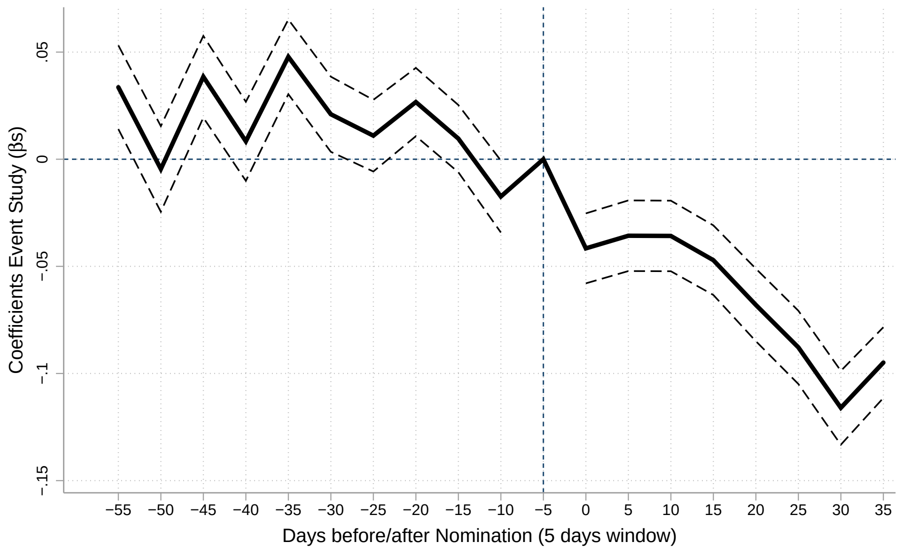
$$\Delta^j_{ih} = \lambda_{ih} + \sum_{t=-60}^{30} \beta_\tau \mathbb{1}(\tau = t) + \epsilon^j_{ih}. \tag{2.5.5}$$

Figure 2.10 reports the coefficients β_τ associated with the combinations between the dummy variables in Equation 2.5.5 when only movies with the same genre and belonging to the same k-mean and k-median clusters are compared. No trends can be detected in the period before the nomination. Still, a slight anticipation effect can be observed.

A possible interpretation for these dynamics can be given by dividing the time window around nominations into three periods. In the first period (until the window $-15/-10$), users are not aware of the identity of potential candidates for the nominations. Thus, they do not get disappointed by movies. Then, after window $-15/-10$, the identity of the potential nominated movies starts to become clear and the disappointment effect starts to affect ratings.

Crucially, this is the period in which the Golden Globes, the second most important awards for movies and TV shows, are assigned. The correlation between movies nominated and awarded with the Golden Globe and nominated movies for the AMPAS awards is very high and this could ignite a shift in users' expectations. Finally, after window 10/15, users' ratings are affected by the official nominations with a further drop.

Figure 2.10: The Event-Study Graph for Δ^j_{ih} around the AMPAS Nominations



Note: The figure shows the dynamics of the parameters β_τ of Equation 2.5.5 around the AMPAS Nominations starting 60 days before until 30 days after. 95% confidence intervals with s.e. clustered at movie and 5-day window level are displayed.

Comparing this graph with the previous ones in Figure 2.7, it is possible to notice that the drop in ratings here is much more significant and of greater magnitude. Therefore, assuming that the new design is able to isolate disappointment, it is possible to conclude that the selection effect positively affects ratings after nomination. In Section 2.4, I present a framework in which this is possible and it may be due to a change in the distribution of the users' utility parameters before and after nominations.

In Appendix 2.9, I present two additional event-study graphs to show evidence in favor of the parallel-trend assumption. Figure B.6 shows the coefficients β_τ once I add all controls and fixed effects to Equation 2.5.3. In Figure B.7, I repeat the same analysis of Figure 2.7 for a longer span of days after the nomination.

In the next Section, I repeat this analysis with two extensions. As for the DiD design, I consider movies receiving a different number of nominations and awards. Conversely, in Section 2.11, I study variations of Δ^j_{ih} around the AMPAS award dates to capture a further disappointment effect related to awarded movies.

2.6 Results

In this Section, I show the numerical results for the two identification strategies described before. Following the structure in Section 1.4, first I describe the results for the DiD design; then, I move to the results of the second strategy adding the movie matching with the cluster algorithms to the DiD approach.

2.6.1 Difference-in-Difference

As highlighted in the previous Section, disappointment and selection effects cannot be disentangled with the DiD design. This identification strategy can credibly show whether the AMPAS nominations affect movie ratings, but it is silent regarding the source of this change. Table 2.3 shows the main results presenting nine different specifications and restricting on a window of 30 days before and after the nominations. A wider window (60 days before and after) is reported in Table B.3. Different fixed effects are added in Columns 1-5; whereas, in Column 6 I add the following time-invariant controls: $US - Release_i$, $US - Production_i$ and $English - Language_i$; $Director - Nominated_i$, $Director - Awarded_i$, $Stars - Nominated_i$, and $Stars - Awarded_i$. In Columns 7-9, movie and user fixed effects are present and only time-varying controls can be identified. The results show that the main parameter of interest (the interaction $Nom_i \times T_{ij}$) is negatively significant and stable across different specifications. Accordingly, after the AMPAS nominations, nominated movies get significantly lower ratings relative to not nominated ones. Although statistically significant, the effect is relatively small if we look at the average ratings for nominated movies (3.73 in Table 1.1). Yet, once this effect is compared with the rating premium for nominated movies (the coefficient for the parameter Nom_i in Table 2.3), its magnitude and economic significance look greater: the drop in ratings for nominated movies in the first 30 days after the AMPAS nomination accounts for five percent of the premium of being a nominated movie. Similar results are present with a wider window of time around the nominations (60 days), as it is shown in Table B.3. To study the heterogeneity of the nomination effect, I report in Table 2.4 three different specifications. In Column 1, I divide nominated movies in two groups: movies that are nominated only for one award (Nom_i^1); and movies that are nominated for more than one award ($Nom_i^{>1}$). Thus, I repeat the same analysis as in Equation 2.5.1 substituting the dummy variable Nom_i with a variable taking three values: not nominated; nominated for one award, and nominated for more than one award.

The coefficient of interest for movies nominated only for one award $Nom_i^1 \times T_{ij}$ is statistically insignificant but still negative. Conversely, the coefficient of interest for movies nominated for more than one award $Nom_i^{>1} \times T_{ij}$ is negative and statistically significant. Moreover, comparing the magnitude of this coefficient with the one obtained in Column 9 in Table 2.3 (with the same specification), it is possible to observe that the coefficient $Nom_i^{>1} \times T_{ij}$ is greater than the one about all nominated movies. In Columns 2 and 3, I restrict the attention to nominated movies receiving at least one AMPAS award. The award ceremonies usually occur around 30-35 days after nominations. Once I restrict my analysis to the first 30 days after nomination (when awards are not yet assigned), the coefficient $Nom_i^{award} \times T_{ij}$ is negative, but not significant (Column 2). In Column 3, I extend the study to 60 days after nominations (so roughly 30 days after awards). Doing so, the parameter turns significant with greater negative magnitude.

The results in Tables 2.3 and 2.4 are in line with the predictions proposed in Section 2.4. In particular, Table 2.3 shows that the increase in expectations due to the AMPAS nominations leads to a significant decrease in ratings. Furthermore, the heterogeneous effects reported in Table 2.4 show that those movies whose expectations receive a greater positive shock (those with a higher number of nominations) experience a more negative drop in ratings after the nominations. In the next Section, I provide further evidence in line with these two observations; and I show that disappointment is the main driving force for the resulting drop in ratings.

Table 2.3: Difference-in-Difference: The Impact of the AMPAS Nominations on r_{ij}

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Nom_i	0.613***	0.573***	0.596***	0.594***	0.568***	0.393***	0	0	0
	(0.0238)	(0.0255)	(0.0258)	(0.0256)	(0.0260)	(0.0259)	(.)	(.)	(.)
T_{ij}	-0.00361	-0.00256	-0.000249	-0.000195	-0.0290***	-0.0267***	-0.0347***	-0.0347***	0.00899
	(0.00797)	(0.00796)	(0.00778)	(0.00781)	(0.00596)	(0.00581)	(0.00507)	(0.00507)	(0.00838)
$Nom_i \times T_{ij}$	-0.0225**	-0.0225**	-0.0274***	-0.0256***	-0.0278***	-0.0282***	-0.0170**	-0.0170**	-0.0178**
	(0.0102)	(0.00989)	(0.00939)	(0.00928)	(0.0103)	(0.0102)	(0.00848)	(0.00848)	(0.00841)
$diff_{ij} \times 100$									-0.140***
									(0.0240)
$\bar{r}_{jt-1}$									0.00229
									(0.0176)
$n_{jt-1} \times 100$									-0.0103***
									(0.00103)
Constant	3.371***	3.379***	3.373***	3.374***	3.390***	3.506***	3.508***	3.508***	3.518***
	(0.0128)	(0.0123)	(0.0120)	(0.0118)	(0.0103)	(0.0306)	(0.00212)	(0.00212)	(0.0611)
$\boldsymbol{X_{ij}}$						✓			
Genre FE		✓	✓	✓	✓	✓			
Year(Award) FE			✓	✓	✓	✓			
Clusters FE				✓	✓	✓			
User FE					✓	✓	✓	✓	✓
Movie FE							✓	✓	✓
R^2	0.0544	0.0622	0.0647	0.0655	0.290	0.300	0.418	0.418	0.420
Observations	390213	390212	390212	389856	385842	385842	384894	384894	382969

Note: In Column 1 I present a specification with no controls or fixed effects. From Column 2 to 5 I add fixed effects referring to the genre (Genre FE), the year of the award (Year (Award) FE), the k-mean and k-median clusters (Clusters FE), and users (User FE) respectively. In Column 6, I add all time-invariant controls grouped in $\boldsymbol{X_{ij}}$. From Columns 7 to 9, I add user and movie fixed effects (Movie FE) together with time-invariant controls. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. I restrict on a time window of 30 days before and after the Academy Nominations. Cluster standard errors at the movie and 5-day window level are in parentheses. After adding movie fixed effects, the parameter regarding the variable Nom_i (and all time-invariant controls) cannot be identified due to multicollinearity with the fixed effects.

Table 2.4: Difference-in-Difference: The Impact of the AMPAS Nominations on r_{ij} for Different Nominated Movies

	(1)	(2)	(3)
$Nom_i^1 \times T_{ij}$	-0.00713		
	(0.0122)		
$Nom_i^{>1} \times T_{ij}$	-0.0249**		
	(0.0110)		
$Nom_i^{award} \times T_{ij}$		-0.00974	-0.0270**
		(0.0116)	(0.0114)
$diff_{ij} \times 100$	-0.140***	-0.140***	-0.101***
	(0.0240)	(0.0240)	(0.0125)
$\bar{r}_{jt-1}$	0.00231	0.00231	0.0188
	(0.0176)	(0.0176)	(0.0155)
$n_{jt-1} \times 100$	-0.0103***	-0.0102***	-0.0105***
	(0.00103)	(0.00102)	(0.000905)
Constant	3.518***	3.518***	3.488***
	(0.0612)	(0.0611)	(0.0549)
User FE	✓	✓	✓
Movie FE	✓	✓	✓
R^2	0.420	0.420	0.410
Observations	382,969	382,969	574,004

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. In Columns 1 and 2 I restrict on a time window of 30 days before and after the Academy Nominations. In Column 3, I add further 30 days after the nomination to capture the impact of the awards. Cluster standard errors at the movie and 5-day window level are in parentheses. All three specifications report the full set of controls and fixed effects as in Column 9 in Table 2.3. Column 1 shows results for nominated movies with one nomination only, and nominated movies with more than one nomination. Columns 2 and 3 show results for nominated movies that win at least one AMPAS award.

2.6.2 Difference-in-Difference with Movie Matching

With the second design, I can identify the role of disappointment in the drop of movie ratings due to the AMPAS nominations. To do so, I study variations in the difference Δ_{ih}^{j} before and after the nomination as in Equation 2.5.4. Table 2.5 shows the main results presenting seven different specifications and restricting on a window of 30 days before and after nominations. A wider window (60 days before and after) is used in Table B.4. Columns 1-4 report the specification without adding controls apart from the movie-combination fixed effects. Column 1 does not restrict on movies with similar characteristics and the coefficient of interest may capture disappointment and selection due to the change in users' preferences. Columns 2-4 show results varying the type of not nominated movies compared with the nominated ones.

Table 2.5: Difference-in-Difference with Movie Matching: The Impact of the AMPAS Nominations on Δ_{ih}^{j}

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
T_{ij}	-0.0591***	-0.0584***	-0.0627***	-0.0617***	-0.0635***	-0.0619***	-0.0303***
	(0.00143)	(0.00312)	(0.00355)	(0.00370)	(0.00372)	(0.00372)	(0.00494)
$\bar{r}_{ht-1(j)}$					0.312***	0.300***	0.319***
					(0.0186)	(0.0186)	(0.0187)
$\bar{r}_{jt-1(h)}$					-0.348***	-0.353***	-0.372***
					(0.0260)	(0.0260)	(0.0262)
$\bar{r}_{it-1(j)}$						-0.168***	-0.149***
						(0.0144)	(0.0146)
$\bar{r}_{jt-1(i)}$						0.0870***	0.0869***
						(0.0144)	(0.0147)
$n_{j(h)} \times 100$							0.00461***
							(0.000533)
$n_{j(i)} \times 100$							0.0253***
							(0.00179)
Constant	0.603***	0.577***	0.559***	0.549***	0.849***	1.186***	1.086***
	(0.000702)	(0.00152)	(0.00171)	(0.00178)	(0.121)	(0.123)	(0.125)
Movie-Combination FE	✓	✓	✓	✓	✓	✓	✓
All Movies	✓						
Movies with Same Genre		✓	✓	✓	✓	✓	✓
Movies in Same Cluster (k-mean)			✓	✓	✓	✓	✓
Movies in Same Cluster (k-median)				✓	✓	✓	✓
R^2	0.295	0.288	0.287	0.295	0.295	0.296	0.297
Observations	3,032,937	618,872	449,817	408,709	405,536	405,036	405,036

Note: In Column 1 I present a specification with movie-combination fixed effect, but without restricting to a subsample of movies with similar features. From Column 2 to 4 I restrict to movies with the same genre, and movies belonging to the same genre and and the same k-mean and k-median clusters, respectively. In Columns 6 to 7, I add time-invariant controls to the specification in Column 5. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. I restrict on a time window of 30 days before and after the Academy Nominations. Cluster standard errors at the movie and 5-day window level are in parentheses.

Table 2.6: Difference-in-Difference with Movie Matching: The Impact of the AMPAS Nominations on Δ^{j}_{ih} for Different Nominated Movies

	(Nom_i^1) (1)	$(Nom_i^{>1})$ (2)	(Nom_i^{award}) (3)	(Nom_i^{award}) (4)
T_{ij}	-0.0131	-0.0344***	-0.0213	-0.0337***
	(0.00822)	(0.00639)	(0.0138)	(0.0112)
$\bar{r}_{ht-1(j)}$	0.289***	0.339***	0.335***	0.247***
	(0.0296)	(0.0241)	(0.0524)	(0.0409)
$\bar{r}_{jt-1(h)}$	-0.475***	-0.273***	-0.438***	0.0785*
	(0.0395)	(0.0347)	(0.0984)	(0.0410)
$\bar{r}_{it-1(j)}$	-0.113***	-0.170***	-0.243***	-0.205***
	(0.0250)	(0.0179)	(0.0341)	(0.0266)
$\bar{r}_{jt-1(i)}$	0.0566**	0.103***	0.113***	0.107***
	(0.0250)	(0.0182)	(0.0338)	(0.0269)
$n_{j(h)} \times 100$	0.00776***	0.00283***	-0.00114	0.00495***
	(0.000844)	(0.000691)	(0.00176)	(0.00117)
$n_{j(i)} \times 100$	0.0278***	0.0241***	0.0222***	0.0247***
	(0.00295)	(0.00224)	(0.00423)	(0.00305)
Constant	1.418***	0.742***	1.961***	-0.0666
	(0.188)	(0.167)	(0.449)	(0.223)
Movie-Combination FE	✓	✓	✓	✓
Movies with Same Genre	✓	✓	✓	✓
Movies in Same Cluster (k-mean)	✓	✓	✓	✓
Movies in Same Cluster (k-median)	✓	✓	✓	✓
R^2	0.299	0.285	0.259	0.237
Observations	157,443	247,593	53,235	93,685

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. In Columns 1, 2, and 3 I restrict on a time window of 30 days before and after the Academy Nominations. In Column 4, I add further 30 days after the nomination to capture the impact of the awards. Cluster standard errors at the movie and 5-day window level are in parentheses. All four specifications report the full set of controls and fixed effects as in Column 7 in Table 2.5. Column 1 show results for nominated movies with one nomination only. Column 2 show results considering nominated movies with more than one nomination. Columns 3 and 4 show results for nominated movies that win at least one AMPAS award.

In Column 2, I consider movies with the same genre; in Columns 3 and 4, with the same genre and belonging to the same clusters (using the k-mean and k-median algorithms). Accordingly, these estimates should further remove selection and identify the disappointment effect alone. In the remaining columns, I report results adding further controls for movies and users characteristics: $\bar{r}_{jt-1(h)}$, $\bar{r}_{jt-1(i)}$, $\bar{r}_{ht-i(j)}$, $\bar{r}_{it-i(j)}$, $n_{jt-1(h)}$, and $n_{jt-1(i)}$. All other controls used in the previous design cannot be considered here since all movie-specific variables vanish by the presence of the movie-combination fixed effects. All specifications show negative and significant results for the coefficient of interest. In this sense, disappointment is the major driving force in the drop of ratings after nominations: when the selection channel is reduced (if not totally removed), the coefficients keep being negative and significant. Comparing these results with the ones obtained with the DiD design, it is possible to claim that selection seems to shift upward ratings after nominations.

Similar results are present with a wider window of time around the nominations (60 days), as it is shown in Table B.4. Moreover, as it is shown in Figure 2.10, the disappointment effect is characterized by a short anticipation since the drop in ratings starts five-ten days in advance relative to the nomination dates. This may be due to the release of relevant information about the potential candidates for the AMPAS awards a few days before the actual nominations.[17] Furthermore, the lag between the effect observed in Figure 2.10 and the one in Figure 2.7 about the DiD design suggests again that the selection effect should not significantly drive the drop in ratings and it may actually have a positive effect.

A further difference between the results of the two designs regards the magnitude of the estimated effect. In the previous Subsection, the coefficient of interest results to be negative and significant. The short-run drop in ratings due to nominations is, on average, 0.02 stars. As reported in the previous Subsection, this accounts for almost five percent of the rating premium for nominated movies. With this second strategy, the disappointment effect driven by nominations almost triplicates, reaching 0.06 stars, on average. This implies that, in the first 30 days after nominations, the rating premium for nominated movies may drop by more than ten percent because of disappointment. This result may be of importance for movie studios (and in general, for sellers with a product portfolio) producing movies with different qualities and likelihoods to receive a quality certification such as the AMPAS awards.

I conclude this Section commenting on the results about different types of nominated movies shown in Table 2.6. Similarly to the analysis of the previous design, Column 1 and 2 report the results of the regression in Equation 2.5.5 selecting nominated movies that received only one, and more than one nominations, respectively. Differently, I select movies that receive the AMPAS awards in Column 3 and 4. In Column 3 I consider only 30 days before and after nominations - when movies are not yet awarded; whereas in Column 4 I study 60 days after nominations. The results of this heterogeneity analysis are similar to the ones reported for the DiD design. Yet, here the difference in coefficients is less significant with respect to the variation reported in Table 2.4.[18] However, in line with the previous results, the magnitude of the variation of Δ^j_{ih} is greater (more negative) for those movies that are nominated for more than one award. Accordingly, it is possible to claim that, when the increase in expectations is greater, the greater is the drop in ratings. Finally, as in the previous design, ratings for awarded movies seem to drop after nomination but only considering a longer span after the nomination dates. In Appendix 2.11 , I elaborate on this last result and I propose a new methodology to identify the disappointment effect associated with the AMPAS awards. Here I use nominated movies that are not awarded as a control group for nominated movies receiving an award. Both groups received the previous shocks on expectations by the nominations, but only those receiving at least one award are treated by a new shock that trigger further disappointment. The estimates show that also the AMPAS awards negatively impact ratings for awarded movies in line with the theoretical framework.

[17] As supporting evidence for this phenomenon, it is worth recalling that there is a flourishing betting activity over AMPAS awards and nominations.

[18] The not nominated movies used to compute the difference Δ^j_{ih} differ across columns making the comparison more difficult.

2.7 Conclusion

This paper shows empirical evidence supporting the importance of reference points in agents' utility. In particular, I identify the disappointment effect in users' utility related to the increase in expectations due to a quality disclosure. The context of my analysis regards movie ratings displayed by users on an online recommender system (MovieLens). The Academy of Motion Picture Arts and Sciences awards' nomination is the main quality disclosure event that shifts (upward) users' expectations about movies. The results show that ratings for nominated movies drop after nominations, and disappointment due to the rise of expectations is the main driver for such a drop. Moreover, nominated movies that are awarded experience a further drop triggered by a second increase in expectations.

I propose two identification strategies: first, I use a DiD design to show that nominations have a negative and significant impact on ratings of nominated movies. To do that, I restrict my analysis over a short window of time around the AMPAS nominations and I compare the variations in ratings for nominated and not nominated movies before and after the nominations. This strategy relies on a parallel trend assumption regarding the evolution of ratings for the two groups of movies (nominated and not nominated). I provide evidence in favor of such assumption studying the rating variations for both groups before the shift in expectations. Results show that nominated movies' ratings experience a drop right after nomination equivalent to five percent of the premium they have in terms of ratings against not nominated movies. This drop may be due to the disappointment faced by users after an increase in expectations; or a change in the characteristics of users who watch and rate the movies after the nominations.

The second identification aims to disentangle disappointment from selection, studying the difference in ratings by the same user between nominated and not nominated movies. I use unsupervised learning techniques (k-mean and k-median algorithms) to cluster movies with similar characteristics. In this way, comparing movies in the same cluster, the users' selection effect is highly reduced and variations in the rating difference before and after the nomination can solely capture the disappointment effect. This analysis confirms the drop in ratings of nominated movies after the nominations and it suggests that users' disappointment is a relevant driver for this drop.

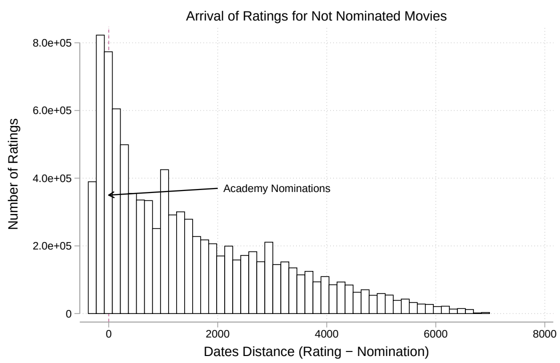
I conclude here with a comment on the results and on their relevance. Certifications and quality disclosures are effective tools to reduce buyers' uncertainty; still, the resulting shift in expectations may partially backfire creating disappointment side-effects in users. With this paper, I show evidence regarding the existence and relevance of disappointment effects after a quality disclosure announcement.

I claim that this result is important and policy-relevant since it shows a further unexplored limitation of certifications, and it documents the relevance of reference points in agents' utility in a new framework. In line with these results, new research avenues may be explored in terms of applications for reference-based preferences in different settings, and regarding the optimal implementation of quality disclosures.

Appendix B

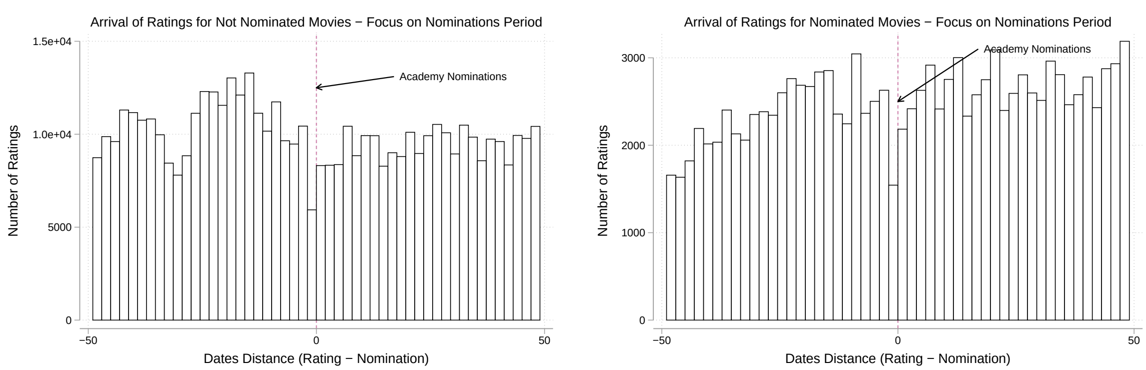
2.8 Appendix: Empirical Setting and Dataset

Figure B.1: Arrival of Ratings for Not Nominated and Nominated Movies (All)



Note: The two figures show the total amount of ratings that are displayed over time for all not nominated and nominated movies. On the x-axis, time is measured in terms of days of distance from the nomination dates.

Figure B.2: Arrival of Ratings for Not Nominated and Nominated Movies (Nominations Period)

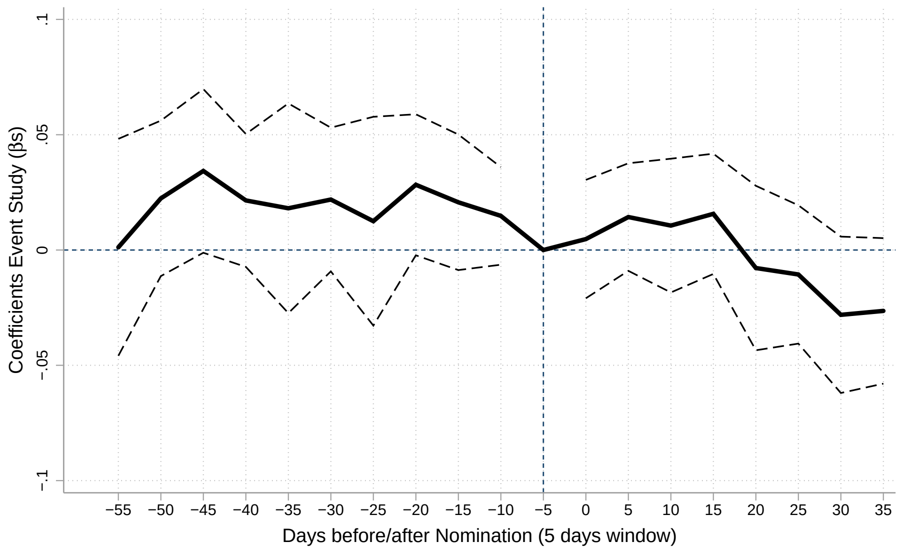


Note: The two figures show the total amount of ratings that are displayed over time for all not nominated and nominated movies. On the x-axis, time is measured in terms of days of distance from the nomination dates.

2.9 Appendix: Identification Strategy

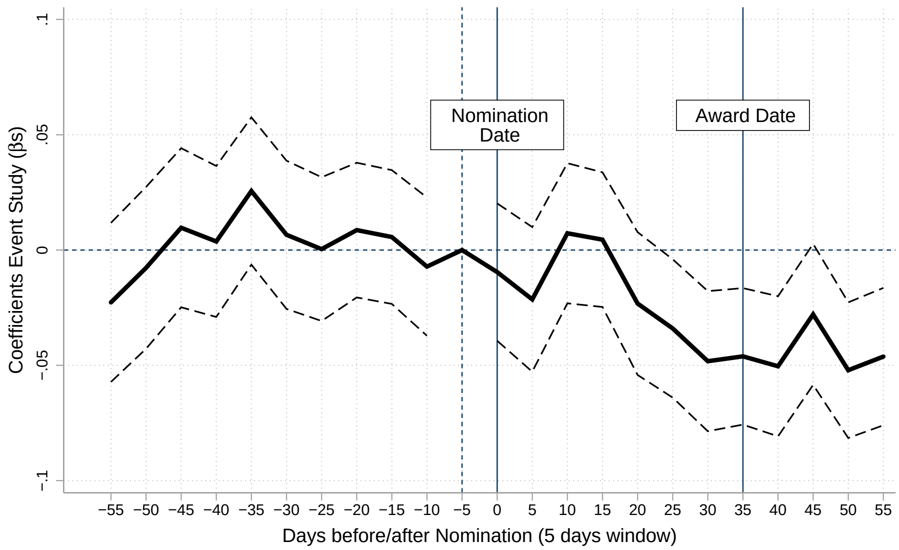
2.9.1 Difference-in-Difference

Figure B.3: The Event Study Graph around the AMPAS Nominations (full controls)



Note: The figure shows the dynamics of the parameters β_τ of Equation 2.5.3 adding all controls as in the column (9) of Table 2.3 around the AMPAS Nominations starting 60 days before until 30 days after. 95% confidence intervals with s.e. clustered at movie and 5-day window level are displayed.

Figure B.4: The Event Study Graph around the AMPAS Nominations (longer span)



Note: The figure shows the dynamics of the parameters β_τ of Equation 2.5.3 around the AMPAS Nominations starting 60 days before until 60 days after. 95% confidence intervals with s.e. clustered at movie and 5-day window level are displayed.

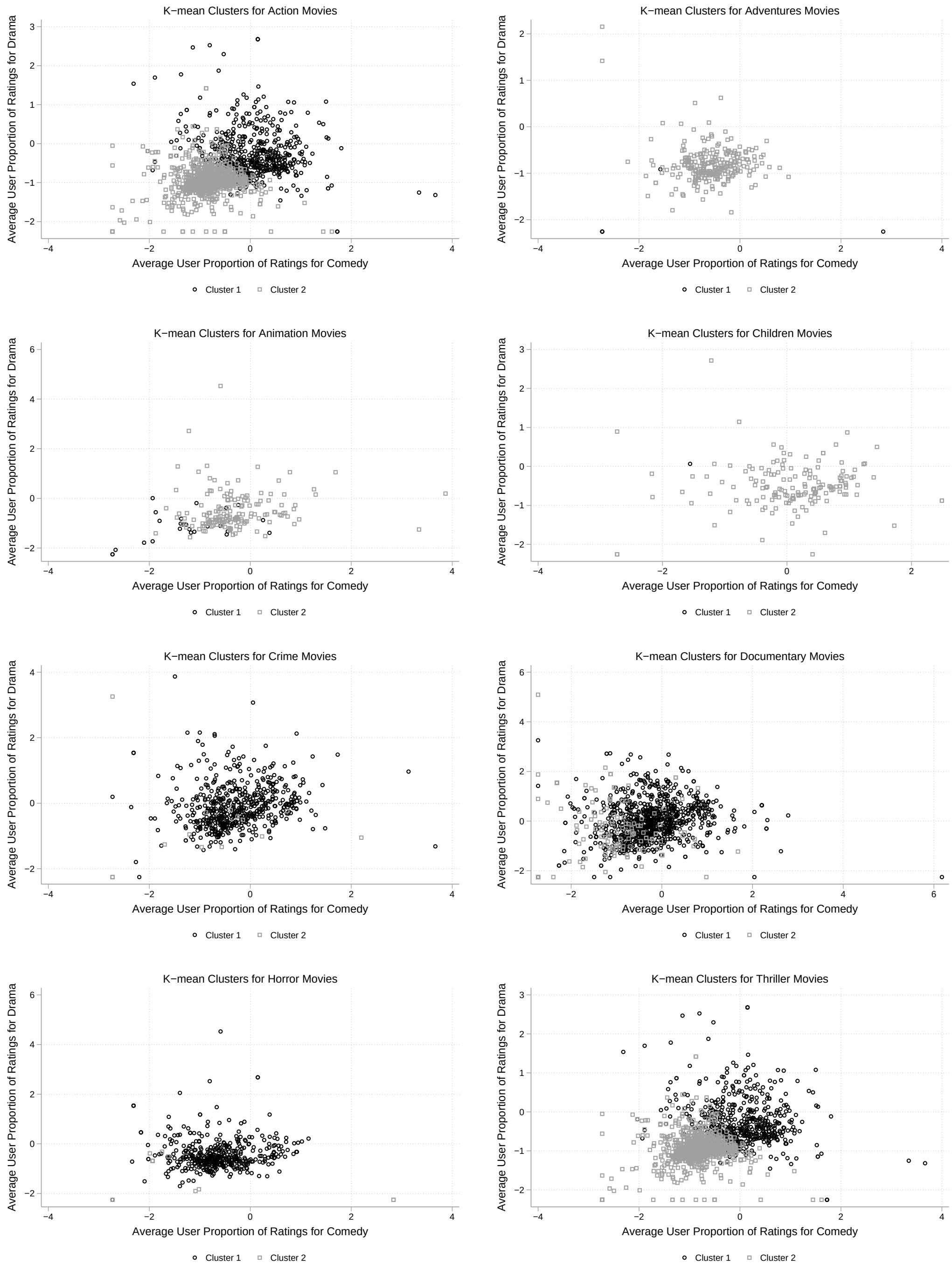
Table B.1: Placebo Difference-in-Difference: The Impact of the AMPAS Nominations on r_{ij} Anticipating the Nominations by 30 Days

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Nom_i	0.614***	0.576***	0.603***	0.598***	0.589***	0.405***	0	0	0
	(0.0288)	(0.0299)	(0.0298)	(0.0292)	(0.0272)	(0.0271)	(.)	(.)	(.)
T_{ij}^{-30}	-0.0190**	-0.0180*	-0.0145*	-0.0148*	-0.0112	-0.0135*	-0.0304***	0.00804	0.0107
	(0.00916)	(0.00912)	(0.00830)	(0.00831)	(0.00805)	(0.00769)	(0.00570)	(0.0106)	(0.0105)
$Nom_i \times T_{ij}^{-30}$	-0.00351	-0.00477	-0.00852	-0.00553	-0.0187	-0.0200	-0.0140	-0.0153	-0.0184
	(0.0131)	(0.0132)	(0.0129)	(0.0130)	(0.0122)	(0.0144)	(0.00943)	(0.00947)	(0.00994)
$diff_{ij} \times 100$								-0.141***	-0.138***
								(0.000294)	(0.000275)
$\bar{r}_{jt-1}$									0.00223
									(0.0152)
$n_{jt-1} \times 100$									-0.00839***
									(0.00120)
Constant	3.392***	3.398***	3.392***	3.393***	3.391***	3.528***	3.503***	3.441***	3.462***
	(0.0142)	(0.0137)	(0.0128)	(0.0124)	(0.0113)	(0.0329)	(0.00220)	(0.0136)	(0.0543)
$\boldsymbol{X_{ij}}$						✓			
Genre FE		✓	✓	✓	✓	✓			
Year(Award) FE			✓	✓	✓	✓			
Clusters FE				✓	✓	✓			
User FE					✓	✓	✓	✓	✓
Movie FE							✓	✓	✓
R^2	0.0490	0.0577	0.0603	0.0616	0.286	0.297	0.420	0.420	0.419
Observations	376,133	376,133	376,133	376,133	372,214	372,214	370,776	370,776	384,001

Note: In Column 1 I present a specification with no controls or fixed effects. From Column 2 to 5 I add fixed effects referring to the genre (Genre FE), the year of the award (Year (Award) FE), the k-mean and k-median clusters (Clusters FE), and users (User FE) respectively. In Column 6, I add all time-invariant controls grouped in $\boldsymbol{X_{ij}}$. From Columns 7 to 9, I add user and movie fixed effects (Movie FE) together with time-invariant controls. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. I restrict on a time window of 60 days before the Academy Nominations. Cluster standard errors at the movie and 5-day window level are in parentheses. After adding movie fixed effects, the parameter regarding the variable Nom_i (and all time-invariant controls) cannot be identified due to multicollinearity with the fixed effects.

Cluster Analysis: k-mean and k-median Algorithms

Figure B.5: K-mean Movie Clusters for the Eight Most Present Genres



Note: The figures show scatter plots of movies belonging to different genres over the variables $\bar{p}_i^{Drama}$ and $\bar{p}_i^{Comedy}$ (standardized). Each dot correspond to a movie and the movies are divided in two clusters following the k-mean algorithm.

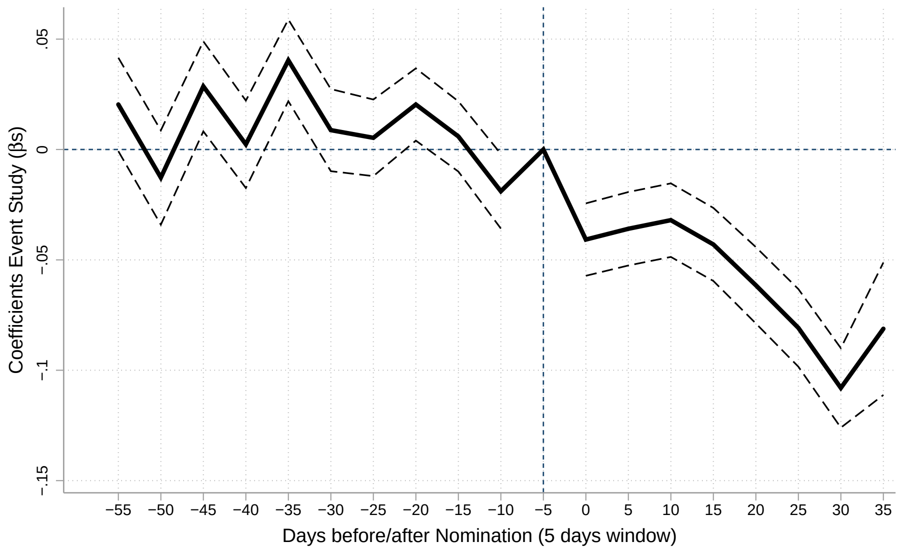
2.9.2 Difference-in-Difference with Movie Matching

Table B.2: Summary Statistics: Users who have rated at least one Nominated Movie (group used in the second design) and All Users

	Users (second design)		All Users	
	(1)	SD	(2)	SD
Average Ratings for Users	3.52	0.44	3.54	0.45
Number of Ratings by Users	68.96	111.022	59.31	96.99
Proportion of Genres (%)				
Action	7.01	-	8.56	-
Adventure	6.32	-	4.68	-
Comedy	24.35	-	26.87	-
Drama	22.26	-	25.41	-
Others	40.06	-	34.48	-
Number of users	1,672	-	2,307	-
Number of ratings	346,029		390,213	-

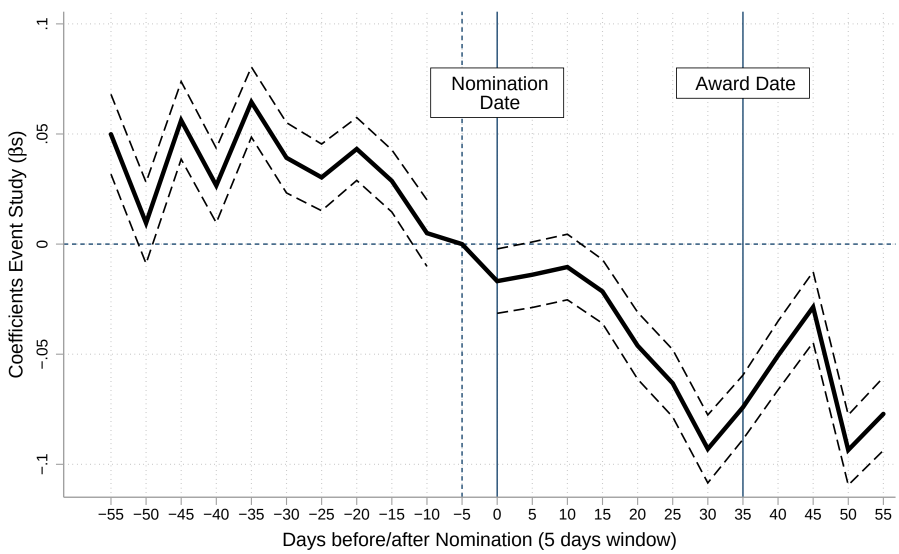
Note: The table shows and compares users who have rated at least one nominated movies (group used in the second design) and all users in terms of average ratings, number of ratings, and genres of the rated movies. All statistics refer to the period around nominations (30 days before and after). All ratings are considered for all not nominated and nominated movies if their first rating is displayed on the platform in the first two years after the year of production.

Figure B.6: The Event-Study Graph for Δ_{ih}^{j} around the AMPAS Nominations (full controls)



Note: The figure shows the dynamics of the parameters β_τ of Equation 2.5.5 around the AMPAS Nominations adding all controls as in the column (7) of Table 2.5 starting 60 days before until 30 days after. 95% confidence intervals with s.e. clustered at movie and 5-day window level are displayed.

Figure B.7: The Event-Study Graph for Δ_{ih}^{j} around the AMPAS Nominations (longer span)



Note: The figure shows the dynamics of the parameters β_τ of Equation 2.5.5 around the AMPAS Nominations starting 60 days before until 60 days after. 95% confidence intervals with s.e. clustered at movie and 5-day window level are displayed.

2.10 Appendix: Results

Table B.3: Difference-in-Difference: The Impact of the AMPAS Nominations on r_{ij} with Extended Window of Time

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Nom_i	0.612***	0.573***	0.607***	0.603***	0.579***	0.407***	0	0	0
	(0.0251)	(0.0265)	(0.0265)	(0.0261)	(0.0260)	(0.0258)	(.)	(.)	(.)
T_{ij}	0.00334	0.00452	0.00646	0.00672	-0.0268***	-0.0274***	-0.0431***	0.00350	0.00415
	(0.00847)	(0.00827)	(0.00756)	(0.00758)	(0.00617)	(0.00606)	(0.00408)	(0.00589)	(0.00583)
$Nom_i \times T_{ij}$	-0.0284*	-0.0283*	-0.0391***	-0.0407***	-0.0543***	-0.0542***	-0.0327***	-0.0339***	-0.0343***
	(0.0149)	(0.0145)	(0.0136)	(0.0127)	(0.0124)	(0.0119)	(0.00791)	(0.00801)	(0.00797)
$diff_{ij} \times 100$									-0.0807***
									(0.00922)
$\bar{r}_{jt-1}$									0.0250*
									(0.0136)
$n_{jt-1} \times 100$									-0.00938***
									(0.000844)
Constant	3.382***	3.389***	3.382***	3.383***	3.403***	3.520***	3.522***	3.500***	3.444***
	(0.0128)	(0.0122)	(0.0117)	(0.0114)	(0.0104)	(0.0316)	(0.00186)	(0.00252)	(0.0487)
$\boldsymbol{X_{ij}}$						✓			
Genre FE		✓	✓	✓	✓	✓			
Year(Award) FE			✓	✓	✓	✓			
Clusters FE				✓	✓	✓			
User FE					✓	✓	✓	✓	✓
Movie FE							✓	✓	✓
R^2	0.0515	0.0592	0.0628	0.0629	0.279	0.289	0.403	0.403	0.404
Observations	769,748	769,748	769,748	767,813	761,769	761,769	762,635	762,635	757,886

Note: In Column 1 I present a specification with no controls or fixed effects. From Column 2 to 5 I add fixed effects referring to the genre (Genre FE), the year of the award (Year (Award) FE), the k-mean and k-median clusters (Clusters FE), and users (User FE) respectively. In Column 6, I add all time-invariant controls grouped in $\boldsymbol{X_{ij}}$. From Columns 7 to 9, I add user and movie fixed effects (Movie FE) together with time-invariant controls. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. I restrict on a time window of 60 days before and after the Academy Nominations. Cluster standard errors at the movie and 5-day window level are in parentheses. After adding movie fixed effects, the parameter regarding the variable Nom_i (and all time-invariant controls) cannot be identified due to multicollinearity with the fixed effects.

Table B.4: Difference-in-Difference with Movie Matching: The Impact of the AMPAS Nominations on Δ_{ih}^{j} with Extended Window of Time

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
T_{ij}	-0.0803***	-0.0761***	-0.0766***	-0.0762***	-0.0758***	-0.0744***	-0.0469***
	(0.00110)	(0.00244)	(0.00278)	(0.00285)	(0.00288)	(0.00288)	(0.00377)
$\bar{r}_{ht-1(j)}$					0.301***	0.292***	0.312***
					(0.0141)	(0.0140)	(0.0141)
$\bar{r}_{jt-1(h)}$					-0.0792***	-0.0800***	-0.103***
					(0.0143)	(0.0143)	(0.0144)
$\bar{r}_{it-1(j)}$						-0.173***	-0.155***
						(0.0105)	(0.0106)
$\bar{r}_{jt-1(i)}$						0.104***	0.102***
						(0.0105)	(0.0107)
$n_{j(h)} \times 100$							0.00491***
							(0.000376)
$n_{j(i)} \times 100$							0.0228***
							(0.00159)
Constant	0.618***	0.586***	0.571***	0.561***	-0.161**	0.110	0.00886
	(0.000575)	(0.00126)	(0.00142)	(0.00144)	(0.0744)	(0.0755)	(0.0769)
Movie-Combination FE	✓	✓	✓	✓	✓	✓	✓
All Movies	✓						
Movies with Same Genre		✓	✓	✓	✓	✓	✓
Movies in Same Cluster (k-mean)			✓	✓	✓	✓	✓
Movies in Same Cluster (k-median)				✓	✓	✓	✓
R^2	0.264	0.256	0.253	0.261	0.261	0.263	0.264
Observations	5,715,672	1,146,118	825,171	743,558	736,830	735,593	735,593

Note: In Column 1 I present a specification with movie-combination fixed effect, but without restricting to a subsample of movies with similar features. From Column 2 to 4 I restrict to movies with the same genre, and movies belonging to the same genre and and the same k-mean and k-median clusters, respectively. In Columns 6 to 7, I add time-invariant controls to the specification in Column 5. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. I restrict on a time window of 60 days before and after the Academy Nominations. Cluster standard errors at the movie and 5-day window level are in parentheses.

2.11 Appendix: Disappointment and AMPAS Awards

Until now, I exploit the AMPAS nomination dates as the shock in users' expectations. However, the AMPAS award dates may also trigger disappointment by increasing users' expectations. To show this, I repeat the event study analysis in Equation 2.5.5 for two categories of nominated movies: those who are awarded, and those that are not. Still, now I consider the dynamics of Δ^j_{ih} around the AMPAS award dates. Figures 2.5 and 2.6 show the estimated coefficients β_τ for awarded and not awarded (but nominated) movies. In both figures, a similar negative trend is observable because of the disappointment effect caused by nominations. AMPAS awards are usually assigned 35 days after the nominations. Thus, the drop in Δ^j_{ih} before the award dates is contemporaneous to the nominations. Then, after the award dates, the paths of Δ^j_{ih} for the two categories differ. Δ^j_{ih} continues to drop for awarded movies after the awards.

Conversely, the evolution of Δ^j_{ih} is stable after the awards for those nominated movies that do not receive any award. This discrepancy is again in line with the different signals that movies received. After the AMPAS award is assigned to a movie, users' expectations rise again and they trigger further disappointment. Yet, this is only true for awarded movies.

After observing the two pre-award parallel dynamics of Δ^j_{ih} in the figures above, a new DiD design can be proposed to capture the disappointment related to the AMPAS awards. This is possible using the dynamics for not awarded nominated movies as a counterfactual. The main equation is:

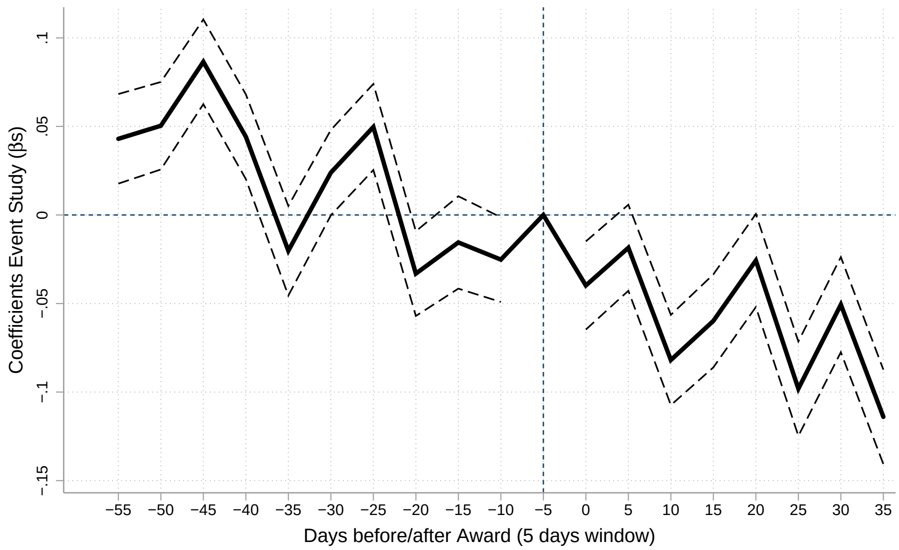
$$\Delta^j_{ih} = \alpha + \lambda_{ih} + \beta_1 T^{award}_{ij} + \beta_2 Award_i \times T^{award}_{ij} + \boldsymbol{\delta X^j_{ih}} + \epsilon^j_{ih}. \tag{2.11.1}$$

The only novelties relative to Equation 2.5.4 are the indicator T^{award}_{ij}, taking value 1 if r_{ij} is displayed after the award date, and 0 otherwise; and the interaction between the dummy variable $Award_i$, selecting nominated movies receiving at least one AMPAS award, and T^{award}_{ij}. Here the coefficient β_2 is supposed to capture the disappointment effect for awarded movies together with the elation for the not awarded nominated movies. To corroborate the presence of pre-award parallel trends among nominated movies, Figure B.10 displays the estimates of the coefficients β_τ for the following regression:

$$\Delta^j_{ih} = \alpha + \lambda_{ih} \sum_{t=-60}^{30} \delta_\tau \mathbb{1}(\tau = t) + \sum_{t=-60}^{30} \beta_\tau Award_i \times \mathbb{1}(\tau = t) + \epsilon_{ij}. \tag{2.11.2}$$

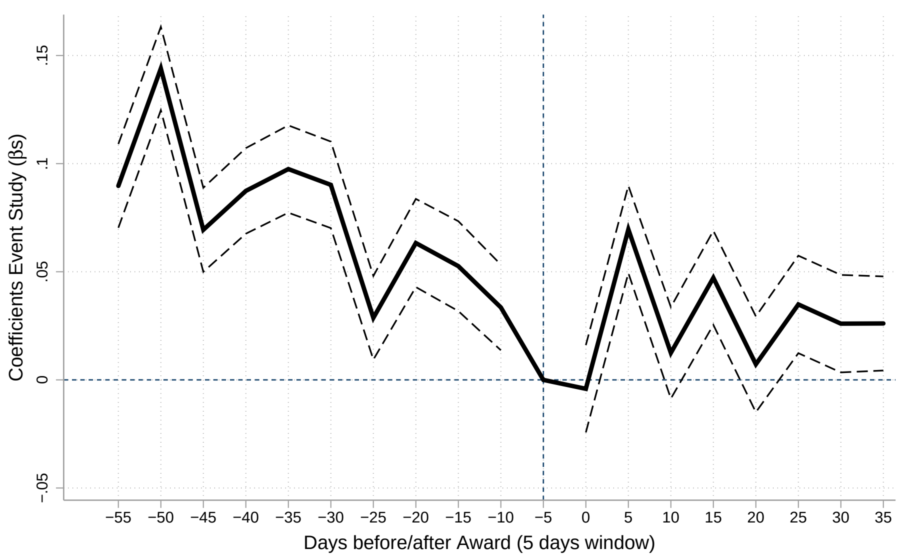
Table B.5 shows the main results presenting seven different specifications and restricting on a window of 30 days before and after the awards (as for the previous design). A wider window (60 days before and after) is used in Table B.6.

Figure B.8: The Event-Study Graph for Δ^{j}_{ih} around the AMPAS Awards for Awarded Movies



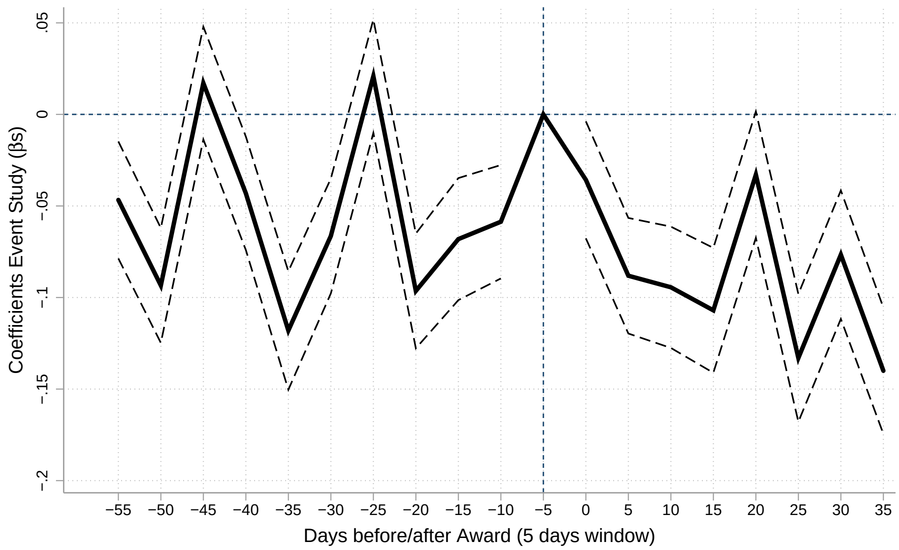
Note: The figure shows the dynamics of the parameters β_τ of Equation 2.5.5 around the AMPAS Awards starting 60 days before until 30 days after. The analysis regards only nominated movies that receive at least an award. 95% confidence intervals with s.e. clustered at movie and 5-day window level are displayed.

Figure B.9: The Event-Study Graph for Δ^{j}_{ih} around the AMPAS Awards for Not Awarded Movies



Note: The figure shows the dynamics of the parameters β_τ of Equation 2.5.5 around the AMPAS Awards starting 60 days before until 30 days after. The analysis regards only nominated movies that do not receive any award. 95% confidence intervals with s.e. clustered at movie and 5-day window level are displayed.

Figure B.10: The Event-Study Graph for Δ_{ih}^{j} around the AMPAS Awards



Note: The figure shows the dynamics of the parameters β_τ of Equation 2.11.2 around the AMPAS Awards starting 60 days before until 30 days after. 95% confidence intervals with s.e. clustered at movie and 5-day window level are displayed.

All specifications show negative and significant results for the coefficient of the interaction $Award_i \times T_{ij}^{award}$. Thus, AMPAS awards seem to increase users' expectations and form a disappointment effect depressing the ratings for awarded movies after awards. Similar results are present with a wider window of time around the awards (60 days), as it is shown in Table B.6.

The magnitude of this effect is indeed similar (if not slightly smaller) relative to the disappointment caused by nominations. Yet, the comparison between these two forms of disappointment has to take into account that this new effect adds to the previous dynamics that were already affected by the nominations.

Accordingly, the disappointment related to the AMPAS nominations and awards depresses the ratings for awarded nominated movies and accounts for more than fifteen percent of the rating premium for award movies.

Table B.5: Difference-in-Difference with Movie Matching: The Impact of the AMPAS Awards on Δ_{ih}^{j}

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
T_{ij}^{award}	-0.0226***	-0.0183***	-0.00175	-0.00276	-0.00914*	-0.00735	-0.0118**
	(0.00173)	(0.00389)	(0.00462)	(0.00483)	(0.00490)	(0.00490)	(0.00493)
$Award_i \times T_{ij}^{award}$	-0.0191***	-0.0227***	-0.0396***	-0.0457***	-0.0467***	-0.0491***	-0.0480***
	(0.00270)	(0.00608)	(0.00715)	(0.00743)	(0.00746)	(0.00745)	(0.00746)
$\bar{r}_{ht-1(j)}$					0.219***	0.212***	0.239***
					(0.0197)	(0.0197)	(0.0199)
$\bar{r}_{jt-1(h)}$					-0.466***	-0.502***	-0.508***
					(0.0599)	(0.0603)	(0.0604)
$\bar{r}_{it-1(j)}$						-0.176***	-0.165***
						(0.0131)	(0.0131)
$\bar{r}_{jt-1(i)}$						0.105***	0.108***
						(0.0132)	(0.0132)
$n_{j(h)} \times 100$							0.00277***
							(0.000206)
$n_{j(i)} \times 100$							0.0196***
							(0.00149)
Constant	0.550***	0.519***	0.498***	0.492***	1.574***	1.983***	1.762***
	(0.000610)	(0.00134)	(0.00156)	(0.00161)	(0.244)	(0.247)	(0.249)
Movie-Combination FE	✓	✓	✓	✓	✓	✓	✓
All Movies	✓						
Movies with Same Genre		✓	✓	✓	✓	✓	✓
Movies in Same Cluster (k-mean)			✓	✓	✓	✓	✓
Movies in Same Cluster (k-median)				✓	✓	✓	✓
R^2	0.284	0.273	0.271	0.279	0.279	0.280	0.281
Observations	3,502,181	685,433	478,328	434,104	432,331	431,490	431,490

Note: In Column 1 I present a specification with movie-combination fixed effect, but without restricting to a subsample of movies with similar features. From Column 2 to 4 I restrict to movies with the same genre, and movies belonging to the same genre and and the same k-mean and k-median clusters, respectively. In Columns 6 to 7, I add time-invariant controls to the specification in Column 5. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. I restrict on a time window of 30 days before and after the Academy Awards. Cluster standard errors at the movie and 5-day window level are in parentheses.

Table B.6: Difference-in-Difference with Movie Matching: The Impact of the AMPAS Awards on Δ_{ih}^{j} with Extended Window of Time

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
T_{ij}^{award}	-0.0470***	-0.0483***	-0.0350***	-0.0359***	-0.0389***	-0.0367***	-0.0422***
	(0.00132)	(0.00294)	(0.00344)	(0.00357)	(0.00359)	(0.00359)	(0.00360)
$Award_i \times T_{ij}^{award}$	-0.0146***	-0.0199***	-0.0336***	-0.0382***	-0.0400***	-0.0414***	-0.0395***
	(0.00211)	(0.00471)	(0.00550)	(0.00566)	(0.00570)	(0.00569)	(0.00570)
$\bar{r}_{ht-1(j)}$					0.207***	0.198***	0.220***
					(0.0130)	(0.0130)	(0.0131)
$\bar{r}_{jt-1(h)}$					-0.202***	-0.208***	-0.194***
					(0.0204)	(0.0204)	(0.0203)
$\bar{r}_{it-1(j)}$						-0.213***	-0.195***
						(0.00989)	(0.00987)
$\bar{r}_{jt-1(i)}$						0.129***	0.132***
						(0.0100)	(0.0100)
$n_{j(h)} \times 100$							0.00403***
							(0.000146)
$n_{j(i)} \times 100$							0.0183***
							(0.00114)
Constant	0.573***	0.546***	0.525***	0.519***	0.606***	0.949***	0.630***
	(0.000390)	(0.000840)	(0.000961)	(0.000979)	(0.0917)	(0.0928)	(0.0933)
Movie-Combination FE	✓	✓	✓	✓	✓	✓	✓
All Movies	✓						
Movies with Same Genre		✓	✓	✓	✓	✓	✓
Movies in Same Cluster (k-mean)			✓	✓	✓	✓	✓
Movies in Same Cluster (k-median)				✓	✓	✓	✓
R^2	0.263	0.254	0.250	0.257	0.257	0.258	0.260
Observations	6,284,457	1,249,205	871,368	795,422	790,305	789,166	789,166

Note: In Column 1 I present a specification with movie-combination fixed effect, but without restricting to a subsample of movies with similar features. From Column 2 to 4 I restrict to movies with the same genre, and movies belonging to the same genre and and the same k-mean and k-median clusters, respectively. In Columns 6 to 7, I add time-invariant controls to the specification in Column 5. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. I restrict on a time window of 60 days before and after the Academy Awards. Cluster standard errors at the movie and 5-day window level are in parentheses.

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